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SAKARYA UNIVERSITY
GRADUATE SCHOOL OF BUSINESS

A PSYCHOMETRIC AND FINANCIAL FACTORS BASED FRAMEWORK SUGGESTION FOR AN INTEGRATED CREDIT RISK ASSESSMENT INFORMATION SYSTEM

DOCTORAL THESIS

Büşra ALMA ÇALLI

Department: Management Information Systems

Supervisor: Prof. Dr. Erman COŞKUN

JULY-2019

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"This thesis has been accepted unanimously / ~~with majority of vote~~ by the following jury on 29/07/2019..

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Prof. Dr. Erman COŞKUN	SUCCESSFUL	
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Prof. Dr. Neşe GÜLER	SUCCESSFULL	
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	T.C. SAKARYA ÜNİVERSİTESİ İŞLETME ENSTİTÜSÜ TEZ SAVUNULABİLİRLİK VE ORJİNALLİK BEYAN FORMU	Sayfa : 1/1

Öğrencinin

Adı Soyadı	:	BÜŞRA ALMA ÇALLI
Öğrenci Numarası	:	1660D54002
Enstitü Anabilim Dalı	:	YÖNETİM BİLİŞİM SİSTEMLERİ
Enstitü Bilim Dalı	:	YÖNETİM BİLİŞİM SİSTEMLERİ
Programı	:	☐ YÜKSEK LİSANS ☑ DOKTORA
Tezin Başlığı	:	A Psychometric and Financial Factors Based Framework Suggestion for an Integrated Credit Risk Assessment Information System
Benzerlik Oranı	:	%7

ENSTİTÜSÜ MÜDÜRLÜĞÜNE

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Tarih: 29/07/2019

İmza:

☐ KABUL EDİLMİŞTİR ☐ REDDEDİLMİŞTİR **EYK Tarih ve No:**	**Enstitü Birim Sorumlusu Onayı**

ACKNOWLEDGEMENTS

I would like to express my personal gratitude to the people who have supported, assisted, encouraged and given guidance during the entire processes related with this dissertation. I would like to thank my supervisor Prof. Dr. Erman COŞKUN who has always provided me appropriate guidance, attentive feedback and remarkable encouragement. In addition to his academic support, he has provided enormous moral support and extensive help for the last five years we have being studied. I have learnt a lot from him about teaching, performing projects and conducting research by means of his thoughtful and constructive feedback during our studies. He has put immense effort for gaining me academic skills and experience. Thank you Prof. Dr. Erman COŞKUN for being a role model for my academic career. My special thanks to my husband Dr. Levent ÇALLI for his patience and extensive encouragement. He contributed to my studies by providing support and worthwhile suggestions regarding the methodological issues. He made life easier for me during the most difficult times by his unconditional support and his deep understanding the stress stemming from PhD process. I am thankful to him for the inspiration, patience and encouragement he has given me all the time. I would also like to thank my extended family for their love and support.

Büşra ALMA ÇALLI

29.07.2019

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ABBREVIATIONS

ACC : Average Accuracy
AHP : Analytic Hierarchy Process
AIC : Akaike Information Criterion
ANN : Artificial Neural Networks
AUC : Area Under Curve
B2B : Business-to-Business
BDSC : Big Data Small Credit
BLC : Behavioural Life cycle Hypothesis
BN : Bayesian Networks
CART : Classification and Regression Tree
CFC : Consideration of Future Consequences
CHAID : Chi-square Automatic Interaction Detector
DA : Discriminant Analysis
DL : Deep Learning
DOE : Design of Experiment
DSS : Decision Support System
DT : Decision Trees
EFA : Exploratory Factor Analysis
EFL : Entrepreneurial Finance Lab
FFM : Five-Factor Model
FICO : Fair Isaac Corporation
FUZZY : Fuzzy Logic
GA : Genetic Algorithms
GDP : Gross Domestic Product
GST : General Strain Theory
ID3 : Iterative Dichotomiser
IoT : Internet of Things
IRR : Internal Rate of Return
IS : Information Systems
IV : Information Value
KMO : Kaiser-Meyer-Olkin
K-NN : K-nearest Neighbour

LOC : Locus of Control
LR : Logistic Regression
MARS : Multivariate Adaptive Regression Splines
MAS : Money Attitude Scale
MFI : Microfinance Institutions
ML : Machine Learning
MLE : Maximum Likelihood Estimation
MLP : Multilayer Perceptron Approach
OLS : Ordinary Least Squares
P2P : Peer-to-Peer Lending
PBC : Perceived Behavioural Control
RF : Random Forests
RMSE : Root Mean Square Error
ROC : Receiver Operating Characteristic
SVM : Support Vector Machines
TPB : Theory of Planned Behaviour
WOE : Weights of Evidence

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Author: Büşra Alma Çallı	**Supervisor:** Prof. Dr. Erman Coşkun
Date: 29.07.2019	**Nu. of pages:** xii (pre text) + 259 (main body) + 29 (app)
Department: Management Information Systems	

Socioeconomic and technological changes together with shift in consumption patterns of individuals have enhanced the demand of credit for the last two decades. Because of remarkable increase in credit demand, lending has begun to generate more income than other operational transactions for banks and other financial institutions. Nevertheless, in the case of careless giving out of loans without proper risk assessment, difficulties in repayment emerge, which results in economic and social losses. Credit scoring models and algorithms in this field have been developed for the purpose of providing automated mechanisms for better and efficient credit granting decisions.

Decision models and algorithms employed uses different parameters and techniques for producing credit scores. Generally, banks target the upper segment consumers for risk mitigation and use generic risk assessment mechanisms depending on financial history of applicants. Nevertheless, credit risk models implemented are not very appropriate for profiling applicants in Turkey because of cultural and social differences. Considering the trends in lending processes in finance sector such as use of alternative data sources for credit risk assessment especially for providing the access of unbanked individuals to credit and for improving accuracy of decision making, a customized system model for credit risk assessment is an important requirement for Turkey.

Hence, within the scope of this dissertation, relevant variables for decision making process, which potentially enhances credit granting, and their weights were determined by qualitative and quantitative research methods. Accordingly, by means of employing classification algorithm, credit risk models were designed and validated for identification of the indicators, and producing quantitative risk estimates. Consequently, theoretical foundation for two-module risk assessment system and a potential supplementary tool involving a psychometric assessment mechanism was proposed.

Keywords: Decision Support Systems, Credit Risk Evaluation, Credit Scoring

Tezin Başlığı: Entegre Kredi Risk Değerlendirme Bilgi Sistemi için Psikometrik ve Finansal Faktörler Temelli Sistem Önerisi	
Tezin Yazarı: Büşra Alma Çallı	**Danışman:** Prof. Dr. Erman Coşkun
Kabul Tarihi: 29.07.2019	**Sayfa Sayısı:** xii (ön kısım) + 259 (tez) + 29 (ek)
Anabilimdalı: Yönetim Bilişim Sistemleri	

Son yıllarda sosyoekonomik ve teknolojik değişimler ile birlikte bireylerin tüketim alışkanlıklarındaki değişim kredi talebini artırmıştır. Kredi talebindeki dikkat çekici artış nedeniyle, borç verme, bankalar ve diğer finansal kurumlar için diğer operasyonel işlemlerden daha fazla gelir getirmeye başlamıştır. Bununla birlikte, kredilerin uygun risk değerlendirmesi yapılmadan dikkatsiz biçimde dağıtılması durumunda, geri ödemede zorluklar ortaya çıkmakta, bu da ekonomik ve sosyal kayıplarla sonuçlanmaktadır. Bu alandaki kredi skorlama modelleri ve algoritmalar, kredi kararlarını daha iyi ve etkin vermek için otomasyona dayalı mekanizmalar sağlamak amacıyla geliştirilmiştir.

Uygulanan karar modelleri ve algoritmalar, kredi skorları üretmek için farklı parametreler ve teknikler kullanmaktadır. Bankalar riski azaltmak için genellikle üst segment tüketicileri hedeflemekte, ve kredi başvurusunda bulunan bireylerin finansal geçmişine dayanarak değerlendirme yapan jenerik risk değerlendirme mekanizmaları kullanmaktadırlar. Bununla birlikte, uygulanan kredi riski modelleri, kültürel ve sosyal farklılıklar nedeniyle Türkiye'deki başvuru sahiplerinin risk profilini çıkarmak için pek uygun değildir. Finans sektöründeki kredi verme süreçlerinde alternatif veri kaynaklarının kullanılması gibi güncel trendleri dikkate alarak, özellikle bankalarla ilişkisi ve finansal geçmişi olmayan bireylerin krediye erişimini sağlamak ve karar vermenin doğruluğunu artırmak için Türkiye özelinde kredi risk değerlendirmesine yönelik bir sistem modeli önemli bir gereksinimdir.

Dolayısıyla, bu tez kapsamında, kredi kararlarını verme süreçlerinde performansı artırma potansiyeline sahip olan değişkenler ve ağırlıkları nitel ve nicel araştırma yöntemleriyle belirlenmiştir. Bu doğrultuda, ilgili parametrelerin belirlenmesi ve nicel risk tahminleri üretmek amacıyla, sınıflandırma algoritması kullanılarak kredi risk modelleri tasarlanmış ve geçerliği test edilmiştir. Sonuç olarak, iki modülden oluşan risk değerlendirme sisteminin teorik temeli ve psikometrik değerlendirme içeren potansiyel bir ek değerlendirme mekanizması önerilmiştir.

Anahtar Kelimeler: Karar Destek Sistemleri, Kredi Risk Değerlendirme, Kredi Skorlama

INTRODUCTION

Socioeconomic changes and the consumption habits of individuals and societies have increased the use of loans for the last years. Depending on the fact that individuals use loans to meet a wide range of needs, lending has begun to generate more income than other operational transactions for banks and other financial institutions. Hence, loans are important for today's economic life. Business and consumer loans when used appropriately have the potential to stimulate the economy and to overcome cash-related difficulties in the markets. However, when used carelessly they cause losses and damage the economy. In Turkey, banks dominating the field aim to distribute as many loans as possible regardless of the social and economic impact of the difficulties in loan repayment. At the same time, long-term processes and bureaucratic procedures at the stage of decision making for loan applications make the process burdensome. In addition, banks mainly targeting the upper segment in order to mitigate the risk constitute a barrier for particular segments' credit access. In order to avoid economic and social losses, financial institutions should evaluate the applications based on scientific approaches and develop appropriate methods and techniques. Credit approval or rejection decisions should be given after determining the risks correctly.

Credit scoring and decision systems in this field were developed for this purpose and algorithms consisting of different parameters and techniques are used for the estimation of risk based credit scores. However, these algorithms are not very compatible to profile loan applicants in Turkey as they do not fit well to social and economic structure and culture of the country. Parameters used in credit score calculations should be customized to reflect the situation in Turkey and the weight of the algorithms should be determined within this particular context. Considering the growth in the field of consumer spending in Turkey, in order to establish the appropriate competitive environment, breaking the dominance of banks in consumer credit sector is important. Therefore, involvement of different institutions in loan and credit card financing is crucial not to experience social and economic disadvantages.

Credit history and financial history have a major impact on the credit decision processes of banks and should support the application process of applicants. However, in developed countries, there are micro-financiers that assess their risks with flexible and quick mechanism to ensure the accessibility of each segment to credit. Microfinance Institutions (MFIs) are those that distribute micro-loans and they aim to make profits by targeting individuals with a low-income group, often with no proven credit history.

Individuals may need loans for many different purposes and there are many different types of loans. Micro-loans are small amounts of loans that can be provided by individuals, credit cooperatives or different investors. The goal is to bring together individuals who cannot reach loans under the strict rules of the banks. Providing small-scale financial support, especially those with low income and no proof of credit history, is seen as a profitable niche market. In this context, meeting the applicants with the appropriate credit and performing these processes at the time of application necessitates flexible decision support systems integrating unconventional data form different sources. Therefore, a customized system which can be both used by banks and other lenders such as micro-financers for the purpose of making accurate and fast risk evaluation is proposed within the scope of this study. Hence, identification of parameters, construction of models and testing them to determine the most appropriate set of parameters are major goals of the study.

One of the problems related to credit scoring in Turkey is the difficulty in accessing accurate data. Therefore, parameters mentioned in the literature may not be realistic for implementation and suitable for Turkey's dynamics. Therefore, the primary objective of the study is to determine the parameters unique to Turkey for usage in credit score calculations.

The objective of the decision support system is to quantify the creditworthiness of individuals through risk assessment. The main pillars of the systems developed for this purpose are credit scoring models and data. There is a growing trend in the field of usage of alternative data sources for supporting decision making processes.

Studies in the literature reveal that considerable potential exists in this field, especially for developing countries. Evaluation of applicants, who do not have credit history or proof of evidence for various reasons, requires integration of data from many different sources. In this context, contribution to literature is made as a customized decision support system architecture. It is aimed to support this system with emerging trends by evaluating the adaptability of the contemporary approaches. One of them, psychometric assessment, referring to determine the character traits, behaviour and attitudes of individuals through various tests is incorporated into the system proposed.

Study Background

The scope of this dissertation is to propose a decision support system to support and guide decision making processes of lenders. In the way of accomplishment, determining the appropriate data, data sources, models and techniques to support the decision flow are major goals. The model to be proposed reveals which indicators, models and techniques should be integrated in order to achieve the best performance. Prior to the proposal of dissertation topic, literature investigations and sector research were conducted. The literature review findings can be summarized as follows: First of all use of alternative methods especially in the case of data scarcity come into fashion. In developing countries, credit scores and credit histories of individuals are uncertain, and therefore, under the bureaucratic processes of banks, many people have no longer access to credit. For enterprises with the potential to lend, there is a need for advanced platforms to support these decisions and different data sources that can be used as an alternative to credit history. The existence of this need has been confirmed during sector investigations and discussions with practitioners.

Secondly, the status and evolution of credit scoring in the literature was investigated and how the processes work especially for lenders were examined. Laha (2007) defined credit scoring as the determination of risk related to credit portfolio and divided it into two groups as application scoring and behavioural scoring. Demographic data of customers is generally used to calculate the application score, while behavioural score is related to past payment performance of customers. Scoring refers to the use of a variety of methods to compute individuals' or institutions' risk based scores in order to make decisions. Scoring is widely used in areas where forecasting is required. Predictive models try to predict the future based on historical data, and in the absence of historical data, judgmental models are used. Credit scoring, on the other hand, means converting data into numerical values using statistical models to support decision making for credit granting. These practices contribute to improving the scope and efficiency of credit distribution systems and increasing the profitability of businesses and financial institutions by effectively reaching a wider customer portfolio (Greenspan, 2002, as cited in Anderson, 2007).

Credit scores can be grouped under different categories including application score, behavioural score, collection score and bureau score. Application score is the score obtained with the demographic data and the other customer information obtained during the application of new customers. While the behavioural score integrates parameters such as past payment performance, account movements, and debt / income status of the customers, the collection score can be used to evaluate the performance of customers' previous repayments. Bureau data is collected by various agencies and provides analysis based on parameters obtained from various channels such as past payment performance of customers, account movements, current debt / limit information (Anderson, 2007). Judgemental decision making techniques used in the past have now been replaced by credit scoring mechanisms and automation of these decision processes. Automated credit processes have the potential to expand the credit customer base by reducing credit portfolio risk (Thomas et al., 2002, as cited in Abdou and Pointon, 2011).

Techniques used in credit scoring models are generally parametric or non-parametric statistical techniques and artificial intelligence approaches (Thomas, 2000, as cited in Lee et al., 2002). Lee et al., (2002) stated that the most commonly used techniques in credit scoring are Discriminant Analysis (DA) and Logistic Regression (LR). Abdou and Pointon (2011) examined the studies focusing on decision making related to loan applications and showed that the methods and techniques applied differ considerably according to the field of application and conditions. Although there is no single approach that performs well under all circumstances, the methods, techniques and indicators to be used should be evaluated and customized according to the context. Anderson (2007) divided the models used in decision making process into four main categories; “judgemental models”, “expert systems”, “hybrid models” and “statistical models”. According to the researcher, expert systems are the most suitable models for situations where the data is not sufficient but there is enough expert experience to define the rules. In contrast, statistical models perform best when data is abundant and structural, and their success largely depends on the availability of the data.

Traditional credit scoring has heavily depended on financial indicators and repayment history of applicants. However, as aforementioned before changes in data sources have also made consideration of other indicators possible in the case of decision making. For instance, psychometric tests revealing behavioural and personality characteristics of individuals and network based indicators have potential to support credit decisions in the case of data scarcity for providing fast decision making.

Psychometric data revealing personality and behavioural characteristics of individuals considered as an alternative source for building credit risk models. In addition to psychometric data, big data consisting of various data types obtained from different channels such as social media and telephone operators has the potential to be used in credit decisions. Factors such as obtained from social networks, work history, contact information, followers and the quality of the contacts are increasingly used in credit risk assessment (Rusli, 2013, as cited in Wei et al., 2015).

Costa, Deb and Kubzansky (2016) highlighted the transformation of consumer credit assessments caused by the digital revolution. In this context, many people in developing economies face problems in accessing official financial services. Today, technology mediates the access of people who are not officially or who cannot formally provide the documents and evidence required to have credit. Mobile call records, bill payments, Internet search history and social media behaviour are considered as a quick and convenient method of providing credit support to these people. The existence of these methods, especially in the distribution of short-term and small-scale consumer loans, has emerged the approach that the authors call “Big Data, Small Credit (BDSC)”. Authors reported that in world's 6 emerging economies (China, Brazil, India, Mexico, Indonesia and Turkey) 325-580 million people have potential to access the credit for the first time.

Klinger, Khwaja and del Carpio (2013) investigated the effect of the use of psychometric tools in the determination of credit risk and concluded that these mechanisms improve the performance of the credit decision process. In many countries, credit bureaus are not developed and it may take time to collect data of potential customers. However, assessments such as Enterprise Finance Lab (EFL) allow for low-cost assessments by reducing information asymmetry, provides additional information and prevents misclassification of loan applicants. Tests such as EFL can be used as a second review mechanism or to increase the number of credits submitted by re-evaluating rejected loan applications. Arráiz, Bruhn and Stucchi (2015) examined the use of the EFL psychometric assessment test in crediting small business owners in Peru. As a result, it was explored that these instruments significantly reduced the credit portfolio risk.

Research Objectives

The broad aim of this dissertation is to propose a conceptual design for supporting credit granting decisions. The decision support system will support the decision making process of decision makers in credit financing. In order to provide this support, the risk assessment of the customers will be realized through the models using data from different sources. The aim is to provide instant and reliable scoring capability by working integrated with different data sources.

Numerous credit scoring models have been developed in the literature. As the economic circumstances and the purpose of crediting change, the models used should show good performance under the existing circumstances as well. Although credit risk assessment mechanisms are an ordinary tool used by banks today, there are almost no customized systems to support the decisions of other enterprises that want to lend. Currently utilised systems are usually in the form of commercial packages that are slightly differentiated from the systems used by banks. However, instant credit support is a completely different process and requires fast decision making with minimum documents from applicants. In addition to other potential lenders, changing circumstances and trends necessitates change in credit evaluation processes of banks as well. Traditional risk assessment is not profitable anymore and to be competitive financial institutions should adopt their systems. Relevant literature mentioned that many individuals who have the potential to take credit in developing countries do not have credit history and cannot access credit due to reasons such as laborious credit processes. Therefore, a credit scoring system will be proposed within the scope of this study in order to fill this gap.

Depending on the arguments above, conceptual system design, which is proposed within the scope of this dissertation, is intended to incorporate credit risk models that integrate alternative data such as psychometrics for providing fast and flexible decision making. In this context, objectives of this dissertation are as follows:

- Identifying modules supporting the credit decision flow within the limits of the system (financial and psychometric modules)

- Determining parameters that the system takes into account for credit risk assessment
- Determining parameters having the most powerful impact on risk estimation by refining these parameters with qualitative and quantitative methods
- Designing and validating credit risk models producing quantitative risk estimates and testing the proposed theoretical models by means of the data set
- Integration of the most appropriate models to ensure consistent and realistic risk assessment

Significance of the Study

Within the scope of the preliminary research carried out for this dissertation, theoretical studies and real world implementations were examined. Models and techniques developed in this context are varied and each performs differently under different conditions. While many studies mention that existing decision support mechanisms are widely used by banks, they are usually in the form of standardized software packages. Commercially available software packages usually undergo some changes in the case of adoption to financial institutions' processes. It is, therefore, necessary to construct customized systems for different contexts. Additionally, utilisation of psychometric indicators is limited to a few tests created in developed countries. Designing a conceptual system model specific to Turkey will contribute to the literature and practitioners in the following ways: There are many individuals, who do not have access for credit in Turkey and there are many enterprises that have the potential to provide credit support to these people. The limitation in this area is the insufficiency of data of these people, especially related with their past payment performance. Therefore, alternative methods can support these individuals' credit application processes. Supporting the traditional models with psychometric evaluation will improve performance of the decision making process. Analysis revealed different set of indicators for estimation of credit risks for the sample investigated compared to previous studies in the relevant field. Psychological indicators were found very powerful in explaining the debt behaviour of participants and these indicators were discovered as a result of combining different qualitative and quantitative research methods which constitute a remarkable contribution for the theoretical work in the field. Psychometric indicators captured are specific to Turkey's dynamics and culture. However, proposed models can be modified for similar cultures and contexts.

Research Approach

Research methodology of this dissertation adopted mixed methods. Qualitative methods were used predominantly for the determination of the parameters for the establishment of the conceptual models. Through these methods, such as interviews and focus group, it was aimed to reveal the problems and requirements related to the field in detail and capture context specific indicators of creditworthiness. Hence, in order to incorporate different facets of creditworthiness into credit risk model, Analytic Hierarchy Process (AHP) of Saaty (1980) was used for defining weights for parameter groups. Systematic review process incorporating content analysis was implemented to double check and synthesize the findings of focus group study and semi structured interviews. Hypotheses and conceptual models constructed were tested by means of applying Logistic Regression analysis. For testing the models, data was collected by means of a well-structured questionnaire and face-to-face administration method. Convenience sampling technique was used to choose participants of the study. Having a response rate of 82%, 425 usable questionnaires were obtained. Hence, ultimate sample size of the study was 425.

Limitations

This study used convenience sampling, which is a kind of non-probability sampling technique aiming to choose the participants based on practical concerns. Although non-probability sampling has limitations due to subjectivity in sample selection and representation of the population, when dealing with large populations it is convenient as randomization is not possible in this case (Etikan et al., 2016). One drawback of this technique is that drawing inferences regarding the whole population is not possible (Saunders, Lewis and Thornhill, 2009). Nevertheless, as no sampling frame was available, probability sampling technique and random sampling could not be implemented for this study. Hence, findings of this study and inferences are limited to the sample within the scope of the study. Because of the length of the questionnaire and to achieve high level of response rate and good quality face-to-face interviews were conducted for implementing the questionnaires. Face-to-face data collection method requires high level of interaction between the interviewer and participant, which required great effort and time. Hence, within the allocated time and budget relatively lower number of respondents (425) completed the questionnaire.

Contributions

New academic publications are expected to be produced in line with the topic of this dissertation. A conference paper was already produced at the first stages of the dissertation proposal. Findings and limitations of the study will increase the amount of scientific production by triggering new academic studies. The study will serve as a good example for the interdisciplinary studies due to its close connection with the fields of management information systems, decision sciences, finance and psychology. The study will also shed light on the studies of other researchers who wish to contribute to the relevant literature and will support the body of knowledge.

Within the scope of this dissertation proposal, in addition to theoretical studies, many patent studies and many systems used in domestic and international applications have been investigated and a requirement in the field has been discovered as a result of changing trends.

Determination of the parameters by using qualitative and quantitative techniques, testing and validating the models are the contribution of the dissertation to the theory. The research in the literature in these fields especially in a developing country context are quite limited and open to development. From a practical point of view, constructing these theoretical models will enable the development of mechanisms that will provide decision support for the practitioners and ensure that the credit distribution is balanced and based on accurate estimates.

The objective of this dissertation is to propose a system model compatible with the end-user profile. In line with this objective, the parameters specific to this system were determined in the light of the specific research methods and included in the model. Type of indicators explored are suitable for this context and models with different components that make risk estimates based on these indicators are the differentiating parts of this study.

Once the theoretical background is established, the conceptual model has the potential to be very useful for the systems that the implementers will develop and implement. The possible economic contribution of the implementation of such a system will be increase in the volume of trade and reduction of expenditures on foreign software platforms to a great extent due to being compatible with the dynamics of the country.

Organization of the Dissertation

This dissertation includes five chapters under the names of Credit Risk Models, Data Sources for Credit Risk Models, Research Design & Methodology, Research Model & Hypotheses and Quantitative Analysis & Findings. This introduction is followed by Chapter 1: Credit Risk Models that starts with history of debt and concepts associated with credit risk assessment. This chapter provides a detailed overview on existing decision support models for credit risk assessment and the techniques used.

Chapter 2 discusses factors utilized for estimation of repayment and default, and provides a comprehensive literature review. Factors discovered in the relevant literature are represented under different categories and explained in detail. Examples from theoretical studies support this section and analysis of findings are clarified. Chapter 3 follows this chapter, and mainly focuses on the explanation of the research philosophy, implemented research methodology and research procedure. Methods applied within the scope of the study such as focus group, semi-structured interviews and pilot study are explained in detail and the foundation for the construction of the research model and hypotheses are justified.

Chapter 4 explains the set of independent variables used for the conceptual model. Under the categories, each independent variable is explained and the rationale behind the decision of including that variable is clarified. The procedure for data coding for classification of individuals and the dependent variable categories are explained. Another section of this chapter introduces hypotheses developed for this dissertation and three (3) proposed models for credit risk decisions. Last section gives information regarding the main survey design issues comprising sampling technique, sample size, sample selection and data collection method. Pilot study procedure and findings of the pilot study are represented and discussed.

Results for the quantitative analysis and findings are represented in Chapter 5. First section of this chapter introduces descriptive statistics of the sample. Second section explaining Exploratory Factors Analysis (EFA) and reliability assessment process and findings, is followed by the third section which explains the analysis results for 3 models. This section also clarifies some concepts associated with Logistic Regression (LR) and its interpretation. First model tested incorporates psychological variables for the assessment of the psychometric component of the decision support system. Second model integrated socioeconomic, demographic and financial variables for construction of the main component and the third model incorporates entire set of variables for testing explanation power of variables when they were taken into account together. Finally, conclusions and recommendations part summarizes findings, main contributions and limitations, and future studies for overcoming the limitations are discussed.

CHAPTER 1: CREDIT RISK MODELS

1.1 History of Debt

After 1980s, there was a significant increase in the percentage of household income, which was spent for loan repayment. Together with the increase in consumer credit utilisation of consumer credit enhanced as well, particularly in the case of low income households. Utilisation of credit by low-income families is an important issue as their access of credit is not easy. In most cases, their applications are more likely to be rejected due to credit risk assessment policies. Those with low-income status may not even consider to apply for credit because they believe that their application will be declined. Moreover, credit policies regarding the low-income families are quite dissimilar with higher interest rates and harder repayment policies. Hence, offering reasonably priced credit for low-income people is important (Zhu and Meeks, 1994).

Credit access is a remarkable opportunity for most people as it facilitates fixing short-term changes in financials and borrowing for long-term purposes such as house purchase. Nevertheless, there are worries regarding the increasing levels of debt recently (Bryan et al., 2010: 7). Financial debt among young adults between 18-30 years old have increased recently. Many studies reported prevalence of problematic debt among young adults (Hoeve et al., 2014).

Debt is considered as the world’s earliest financial mechanism, which should be repaid on schedule independent from the borrower’s situation. Debt is a good way for meeting demand immediately and provide instantaneous cash flow, but in the case of adverse circumstances of financial fluctuations such as recessions, debt can unexpectedly turn into a dangerous economic reality (MFC, 2014: 1). Examining over-indebtedness is important as debt increases gradually. Once individuals go into debt repeatedly, they get involved with more debt until they become financially ruined. Therefore, it is critical to properly manage the risks for credit properly, as credit commitments constitute the huge part of over-indebtedness phenomenon. Excessive debt causes heavy burden of repayment, which may results in defaults. Thus, indicators of over-indebtedness, probability of default, problematic / outstanding debt are inter-related and should be examined in order to profile borrowers with high risk. Those characteristics are multidimensional constituting a complicated phenomenon, which should be anticipated from an interdisciplinary point of view (MFC, 2014).

Examining over-indebtedness within the credit scoring domain is of interest because of the following reasons; First, economic distress caused by debt burden and extent of the difficulty is important for the stability of the financial system. In addition, accumulation of debt and anticipating how it is linked with debt repayment aid in anticipating borrowers' characteristics likely to default (D'Alessio and Lezzi, 2013).

Over-indebtedness indicates a serious financial problem and a remarkable number of over-indebted borrowers exhibit delinquent behaviour because of debt burden. In some cases, when the delinquency continues over a particular period of time, default situation occurs. Thus, devoting attention to over-indebtedness and very high levels of debt / problematic debt / outstanding debt is targeted within the scope of this dissertation for getting sufficient information to construct the credit risk model. Moreover, Bryan et al. (2010: 10) indicated that there are several aspects of over-indebtedness and indicators of the phenomena represent four dimensions including heavy utilisation of credit, perceiving debt as burden, arrears situation and high level of debt repayment amount to income ratio. Therefore, considering research on over-indebtedness domain is likely to capture repayment problems and risky credit behaviour.

Becoming over-indebtedness takes place step-by-step with the accumulation of debt. Most individuals hold short-term debt and repay regularly on time. Financial constraint stage occurs when individuals have high level of debt to income ratio and perceive debt as a heavy burden. Delinquency stage occurs when payments cannot be made on time and indicators of this stage are existence of arrears and utilisation of other loans for handing debt. Emergence of arrears that belong to bills of the living expenses indicates a worse stage of over-indebtedness, and when the amount of debt surpasses total assets, bankruptcy situation occurs. Some people who are permanent debtors demonstrate different inclination towards debt and stereotyped behaviour. Those chronic debtors have some typical personal and behavioural characteristics (MFC, 2014).

Determining over-indebted individuals is a complicated issue and there is not consensus on a specific indicator, which measures over-indebtedness best. However, broadly studies basically mention those four dimensions for measuring the concept; cost of debt (repayment to income ratio), arrears, number of credit commitments and perceived debt burden (D'Alessio and Lezzi, 2013: 5).

Those signals of problematic behaviour should be incorporated into credit risk assessment models of lenders in order to manage credit originated risks properly. Behaviour of creditors should depend on rational and responsible assessments in the case of credit granting in order to prevent over-indebtedness and its socioeconomic impacts on entire financial system (MFC, 2014).

1.2 Consumer Credit

Origins of the consumer credit has its roots in the time of Babylonians (Ntwiga and Weke, 2016) and the concept of borrowing and lending has closely related with human behaviour (Thomas et al., 2002, as cited in Abdou and Pointon, 2011: 59). However, especially over the last 70 years, credit utilisation has become very widespread due to the accessibility in an easy manner (Ntwiga and Weke, 2016). Hence, in spite of the long history of borrowing and lending behaviour credit scoring attempts started nearly sixty years ago (Abdou and Pointon, 2011: 59). Decisions about credit giving is based on credit scores, and lenders utilize different strategies and data sources so as to assign risk based scores for applicants. These risk assessments facilitate meeting the credit with the right customer, which means profit for lenders and elimination of loss stemming from defaults (Tounsi, Hassouni and Anoun, 2017). Credit scoring involves constructing empirical models in order to support decision making (Crook et al., 2007, as cited in Lessmann et al.,2015: 3).

Different loan types such as fixed term loans, rolling or revolving loans exist. Regarding the fixed term loans, loan amount and interest are repaid after a particular time period. Loans that have flexible amount such as credit cards are known as rolling or revolving loans. The characteristics of the loan and preferences determine the length of payment period (Hand and Henley, 1997: 524). Quality of loans is significantly important for banks as they are the major source of profit and contributes being competitive. Hence, decision making in credit management heavily depends on the accurate risk assessments. This evaluation process comprises of analysing and categorisation of various credit components and parameters in order to support decision making (Abdou and Pointon, 2011: 60). Credit scoring is known as the process of estimating probability of defaults of loan applicants. Application scoring is tracking and estimating the repayment behaviour of a borrower to whom loan has already been given (Hand and Henley, 1997: 524).

Regarding the definition of credit scoring Anderson (2007: 3-5) stated that the term credit scoring can be explained separating the term into two. Credit means buying now and paying it later and its origin is the Latin word “credo” inferring to believing. The other work scoring describes the process of assigning numerical values based on some quality criteria in order to rank and distinguish them for the purpose of supporting decision making process (as cited in Abdou and Pointon, 2011: 60). Accordingly, credit scoring is the utilisation of statistical tools to obtain numerical scores from associated data to assist decision making process regarding the credit granting (Abdou and Pointon, 2011: 60). Although the major aim was credit scoring was related with credit risks, recently identification of credit limits, checking for fraud, elimination of loss and delinquency and various loan related services are facilitated by credit granting systems. Depending on the fact that consumer credit is anticipated as their right by consumers, the economy of the century we are living and the credit granting is highly linked with each other. From the aspect of lenders, the decisions of credit allocation holds remarkable risks. However, improvements in terms of technology and automation have considerably transformed the decision making process in the field of credit granting (Anderson, 2007, as cited in Alma and Coşkun, 2017: 310).

Before the credit scoring systems and automation of processes, decisions were dependent on judgemental procedures, which basically compare borrower characteristics with the past loan borrowers’ who performed well in terms of loan repayment. The decision making process was dependent on the subjective evaluation of the credit officer (Crook, 1996, as cited in Abdou and Pointon, 2011: 61). Thus, this process is prone to subjectivity and personal beliefs, attitudes and behaviour of the credit officer, which probably lead to misclassification of applicants, loss of profitability and inaccuracies. Limited number of credits granted and limitations regarding the data availability, also associated with subjective assessment and usage of basic qualitative methods in analysing risk for applicants (Sinkey, 1992, as cited in Šušteršič, Mramor and Zupan, 2009: 4736). In the past, models depending on quantitative techniques was mostly utilised in the case of assessing creditworthiness of business credit applicants because of data availability issues. Legal framework, privacy and security problems in most countries were among the barriers of developing publicly available databases and lenders had to depend on their own databases (Sustersic et al., 2009: 4736). Recently, publicly available databases and credit bureaus collecting data from various channels regarding the loan applicants, analysing and presenting information about this data to the financial institutions make the application of quantitative risk assessments possible.

However, automated decision making processes and quantitative risk estimations provide a robust mechanism for evaluations and quicken the process by elimination bureaucratic steps of credit granting. Credit scoring models also superior to judgemental evaluation as both good and bad loan characteristics are taken into account and bias stemming from focusing bad borrowers only is eliminated. Besides, in contrast to judgemental methods considering parameters that a credit analyst is able to assess and analyse, credit scoring models are capable of dealing with various number of parameters and are constructed on greater sample sizes (Abdou and Pointon, 2011: 61).

1.3 Credit Risk Assessment

Quantification of the process of credit risk assessment provides to cope with the information asymmetry problem, which is encountered when the credit applicants have more insight into their capability of repaying the loan than lenders. However, digital data analysis eliminates the dependence on the data coming from borrowers by widening the scope of data resources and presenting to the lenders (Leyshon and Thrift, 1999, as cited in Poon, 2007: 286).

From sociological aspect, financial innovations may lead gradual increase of debt. Financial institutions offering financial products with non-transparent advertisements and sales strategies complicate the problem. People with low financial education, behavioural proneness and bounded cognitive capacity are not able to make rational decisions in the case of credit utilisation (MFC, 2014).

David (2004) defined the credit risk as the risk of loss emerging from lack of success of loan borrowers in carrying out their responsibilities. Default event, which takes place when the borrower is unable to repay the loan and satisfy the legal obligation is the major element of credit risk (as cited in Ntwiga, 2016: 9). In credit risk domain, concepts of default, delinquency, insolvency and bankruptcy are frequently used in order to define repayment associated problems. Each concept has a different meaning. Default is the name of the situation when an obligation is not met, whereas payment default means that loan borrower do not pay at the due date. Payment default and credit default is associated with the refusal of the loan commitment or delay of the payment for over a period of time. Insolvency is related with inability to repay, while bankruptcy is the name of the formal legal process, which is initiated regarding the defaulted obligators (Ntwiga, 2016: 10). In order to compute default probability many calculations are required and a credit scoring system facilitates to estimate the credit risks in an accurate manner. Credit scores are constructed to evaluate the probability of default of a borrower and to classify the credit borrower based on the quality of the loan (David, 2004, as cited in Ntwiga, 2016: 10).

The most prevalent approaches to credit risk assessment use financial and demographical data. However, lack of financial history of applicants triggered proposal of new methods for evaluating creditworthiness. A remarkable number of research have investigated socioeconomic and behavioural factors behind default probability. Personality factors have also been examined with regard to their link with the repayment behaviour and default. Many factors were found significantly associated with the probability of default, which made way for searching new data sources that reflect personality and behaviour (San Pedro et al., 2015: 197).

Over time, importance of incorporating psychological and economic factors into models for credit risk assessment arose, as default is considered as a time dependent event. Time dependent events are the ways of how borrowers deal with uncertainties in the environment, and anticipating social structures within the network that they interact is important for evaluating their repayment behaviour (Ntwiga, 2016: 11). Changes and trends for creating innovative approaches in credit decision making processed emerged from this motive.

In credit scoring decision support systems, it is important to incorporate willingness to pay of applicants in the process of decision making. Theory of Planned Behaviour indicates that behaviour motive constitutes a major foundation for identifying the behaviour. Hence, probably borrower would not meet the obligations about loan repayment if perceived costs of repayment surpass the associated benefits even though he / she can repay (Lee, 1991; Ajzen, 2008, as cited in Wang, Li and Lin, 2013).

According to Wang et al. (2013) people's willingness to repay is associated with the anticipated worth of trust and prioritising of debt which can be detected by means of past payment behaviour. However, online credit granting decisions has its own characteristics compared to conventional methods mostly dealing with financial data. In this case, e-commerce platform and transactions performed can be utilised. Even though the source of data and its form is different for this case, it still assesses repayment capability and willingness to pay. Hence, in the Internet environment individuals' reputation represents their social capital and is a source of anticipating repayment capability.

Numerous individuals do not have access to credit in developing countries. Initiatives such as increasing the number of institutions or supporting new microcredit lenders have been taken so as to expand credit access. However, physical interaction is expensive and remote access in necessary at most times. Recent credit processes with heavy documentation and heavily dependence on financial indicators exclude approximately two billion individuals around the world who do not have bank account. Nevertheless, up-to-date advancements offer the opportunity of shifting to digital credit granted directly online. Major drivers of digital credit are mobile phones, digital money and behavioural signals that can be captured through digital environment. Incorporation of these technologies makes digital credit possible (Björkegren and Grissen, 2018b: 68)

1.4 Decision Support for Credit Risk Assessment

Data science deals with automated analysis of data by means of specific techniques, procedures and methods for enhancing decision making. Data driven decision making impacts positively on organizations' performance and productivity. Various industries have implemented automated decision making and pioneers of this adoption were finance and telecommunication industries (Provost and Fawcett, 2013: 54). Particularly, banking and finance sector have significantly shifted by the automation after 1990s. Decision making in a highly complicated and dynamic environment as of today's, requires new approaches and techniques for construction of decision support systems (Kabari and Nwachukwu, 2013). Decision support system (DSS) refers to a computer based information system which facilitates decision making issues in managerial and operational levels within a highly complex, uncertain and dynamic environment. As a result increasingly competitive and data intense surroundings, decision makers are faced with a wide range of decision problems. Technological advancements, their fast diffusion and emergence of artificial intelligence techniques have contributed to develop highly elaborate decision support systems that are capable of dealing with risks and uncertainties. DSSs have penetrated a wide range of fields such as medical diagnosis, engineering, finance and banking and traffic control (Kabari and Nwachukwu, 2013: 8).

Credit granting decisions can be performed by banks, financial institutions, building societies, mail order companies, retailers or other organizations who want to lend credit (Hand and Henley, 1997). Basel Committee on Banking Supervision necessitated adoption and utilisation of sophisticated credit scoring systems for risk assessment of financial institutions (Lessmann et al., 2015, as cited in Ala'Raj and Abbod, 2016: 89).

Requirement for credit assessment started with commerce, and borrowing and lending matters (Louzada et al., 2016: 1). Since the beginning of the credit risk assessment in banking sector, banks have used different types of scores for assessing customers such as application scoring, behavioural scoring, collection scoring, attrition scoring, fraud detection, etc. Such scores are computed by gathering data from traditional transaction systems such as Online Transaction Processing, Enterprise Resources Planning or Customer Relationships Management. Basically, data from these systems provide information on some demographic, socioeconomic and financial indicators which is not diverse enough even in developed countries. Recently, focus of financial institutions is on strengthening their processes and infrastructure for improving management of financial risks and credit scoring (Tounsi, Hassouni and Anoun, 2017). Up to date statistical and data mining approaches contributed to the discipline of information science and assessment of the risk level of a particular applicant based on a set of characteristics became possible. Hence, the major rationale behind decision support for credit assessment is to identify parameters that impact on repaying or not repaying and classifying these groups into two so as to accept or reject credit application (Louzada et al., 2016: 2).

Credit risk assessment, construction of models by determining parameters and classification techniques, their performance and efficient loan processing are the major components related with decision making. Algorithms constituting the main elements of models can make the process easier and faster. Depending on the fact that decisions heavily rely on the preferred algorithms, it is critical to anticipate how each algorithm works for particular objectives. In the way of accomplishment, finding the accurate set of variables that are compatible with the algorithm is also crucial. Models do not produce consistent results in terms of accuracy given the same parameter set and model performance is dependent on the set of parameters. Defining the appropriate set of variables within the scope of the business objective and ensuring optimal set of variables are important for efficiency of the decision making process. Transparency is another important issue that should be taken into account as the granted decision and process should be explainable and ethical. Thus, selection of algorithms, selection of parameters, feature selection methods for reducing those parameters are significantly important for the ultimate decision (Addo, Guegan and Hassani, 2018: 2).

1.5 Overview of Recent Trends Influencing Credit Risk Assessment

Consumers' purposes for credit utilisation include house buying, property purchasing and education, which offer them the advantages of social and financial mobility. Hence, credit scores have remarkably affected the utilisation of credit and accessibility, which resulted in inequalities among people. For the last few decades credit scores assisted in credit granting decisions have mostly depended on the financial history. One notable credit score producer is Fair Isaac Corporation (FICO) depends on three financial metrics for producing credit scores. These metrics include amount of debt, length of credit history and payment patterns (regular or irregular). The total weight for these parameters constitutes 80% of the FICO score (Wei, Yildirim, Van den Bulte and Dellarocas, 2015: 1).

Enhancements in Internet connectivity and its rapid implementation in smartphones have provided enrichment of the data gathered through social media platforms. 4G technology facilitated capturing real time movements of users, and as long as the user interacts with the relevant technology data can be retrieved. This makes the usage of non-traditional data available for credit scoring purposes. This data is not limited to social media data and may encompass web searches activities, online financial transactions, location, browser data, technical information, e-commerce transactions and mobile data (Tounsi et al., 2017: 143).

Provost and Fawcett (2013: 54) draw attention to the data processing technologies to support data driven decision making. These up to date technologies consider Big Data and in contrast to conventional data processing systems, they are capable of processing huge amount of data. In order to achieve competitiveness, many companies aim exploring new data sources. For this purpose, data science teams are created to adopt up to date technologies and data mining. In an increasing manner, Digital 100 companies invest in data assets and strategies associated with extracting, organizing and analysing data (Provost and Fawcett, 2013: 55).

1.5.1 Microfinance Sector

Microfinance sector, which considered as a rapid growing industry has become larger over the past ten years. Because of this growth, a considerable number of banks started to function in the microfinance industry (Blanco et al., 2013: 356). Competition in microfinance sector resulting from the industry's booming is very intense, and for long-term survival management of credit risks properly is crucial. Automatic decision support systems eliminate costs of credit evaluations, improve profits and cash flow, minimize risks stemming from losses, fasten decision making and provide close tracking (Cubiles-De-La-Vega et al., 2013: 6910).

Microfinance referring to microcredit as well is a form of banking service offered for the unbanked and low-income individuals that have limited access to credit provided by banks. Institutions that operate in microfinance sector offer small amount of loans having relatively short repayment period. Microfinance provides small amount of loans without burdensome processes unlike banks requesting heavy documentation. Microfinance institutions are geographically concentrated in the developing countries (Kagen, 2018). Microfinance business requires agility in loan granting processes, and most microloans are granted based on online platforms. Thus, efficiency in all processes is crucial and credit risk should be estimated accurately with lowering costs. Consequently, automated decision support systems compatible with microfinance lending provide faster decision making (Blanco et al., 2013: 356).

1.5.2 Peer-to-Peer Lending

Peer-to-peer lending also referring to social lending arose with developments in electronic commerce and emergence of social platforms. This business model facilitates to meet lenders and borrowers on a digital platform by-passing intermediary institutions for instance banks. Thus, higher profits can be expected for both borrowers and lenders. Lending Club in USA stated that popularity of these platforms and their implementations are increasing considerably. Recent platforms are mostly dependent on credit bureau data and conventional scores. However, social lending has its own characteristics compared to traditional risk assessment. Complex behavioural issues also makes the peer-to-peer lending process more complex. Thus, researchers studied on machine learning methods in peer-to-peer lending (Malekipirbazari and Aksakalli, 2015: 4622).

Peer-to-peer lending refers to electronic marketplace that meet borrowers and lenders on an electronic platform, which communicates requests of applicants to the lenders and lenders choose suitable applicants (Serrano-Cinca and Gutiérrez-Nieto, 2016: 114). Serrano-Cinca and Gutiérrez-Nieto (2016) suggested a decision support system (DSS) for peer-to-peer lending. Opposed to classical credit scoring DSS, which focuses on estimating probability of default, researchers considered defaults' profit for lenders. However, correlates of loan profitability were different from those predict probability of default. The suggested approach for estimating the outcome variable, which is internal rate of return (IRR) in this care, was estimated through exploratory analysis, decision trees and multivariate regression.

1.5.3 Social Networks

Ntwiga and Weke (2016) reported changing trends for consumer credit industry such as utilisation of data analytics tools and big data. When the customers' relationship with financial institutions or banks is limited in terms of providing financial history or other traditional indicators of credit risk assessment, big data and social media including user created contents, mobile services, blogs, forums and social networks can be analysed in order to support the credit granting decisions (Siva, 2010, as cited in Ntwiga and Weke, 2016).

Recently new sources of data are investigated to evaluate applicant creditworthiness. Businesses focusing on network-based data (such as Lenddo) have emerged to report credit risk evaluations, which rely on data from the social networking profiles comprising education, employment, number of friends, properties of friends (Rusli, 2013, as cited in Wei et al., 2015: 1). Similar to Lenddo many other companies emerged with the aim of generating credit risk evaluations so as to offer credit opportunities for low-income applicants (Wei et al., 2015: 1).

Social media generates a huge amount of data continuously at a very high speed and availability of data offers the advantages of developing credit risk models by gathering and processing customer related information. Advanced data mining tools for big data and user created content support exploring signals of creditworthiness. For instance, social network of individuals reflecting their friends, relationships, family and the people they communicate is important in enriching lending decisions (Ntwiga and Weke, 2016). Moreover, online trading websites can aggregate, process and analyse customers' past behaviour, and facilitate exploring attributes and behaviour of customers within the network. One successful implementation is conducted by eBay through a feedback forum, which gathers and analyses characteristics and behaviour of the individuals within the social network (Resnick et al., 2000, as cited in Ntwiga and Weke, 2016).

Access of no-file or thin-file individuals to financial services is limited especially in the case of developing countries. Existence of immigrants, new university graduates and people who have not interacted with any of the financial institutions or banks somehow have induced a significant number of individuals without credit scores. According to World Bank statistics nearly 2.5 billion individuals who are not able to get financial services due to this thin-file problem (San Pedro et al., 2015: 196).

For the last two decades, banking sector has experienced a number remarkable change. First of all, nowadays sector is very competitive, and it demonstrates high level of sensitivity to political and economic situations all over the world. In this setting, contrast to traditional strategy focusing on decreasing costs and increasing profitability, banks seek for new ways of eliminating credit risks (Tounsi et al., 2017) and enlarging their customer portfolio. As previously mentioned, social networks offer large amount of data available in a non-structured format which makes accessing to a wide range of users and young people. Big Data analytics and advanced technologies in processing and analysing this type of data provide extracting useful information for evaluating customer creditworthiness. Nature of Big Data comprising volume, velocity, variety, variability and complexity has great potential for improving the credit risk assessment (Tounsi et al., 2017).

Social networks gather enormous amount of data regarding the people's behaviour. The data in social networks are highly unstructured but when accumulated and properly analysed it has potential to better identify the credit scores of people. For instance, income pattern of credit applicants can be detected through analysing locations they travel. For scorecard development, there are ratios determined for locations and countries, which impact on the extent of creditworthiness (Masyutin, 2015: 15).

Guo et al. (2016) conducted a study in China to analyse profiles of a local social network called Weibo and extract features for credit scoring. Researchers used some tweet features, network features and high level features extracted from other features in addition to some demographical data in order to predict default probability of loan borrowers. Significant parameters included in the final models were tweet features comprising retweet behaviour, emoticon and mention utilisation, and positing time. Regarding network features, number of followers, number of friends, fraction of followers that are also followees, fraction of followees that are also followers, fraction between number of followers and followees were selected by relevant algorithms so as to predict probability of default (Guo et al., 2016).

1.5.4 Psychometric Assessment

Psychometric tools are considered as an alternative method that enhances predictive performance of credit scoring systems. Depending on the fact that, in predicting probability of default some psychometric traits had a lower level of difference among countries and various financial institutions, such variables have capability of providing results that are more reliable rather than other demographic or socioeconomic indicators. For instance, Klinger et al. (2013: 87) indicated that conscientiousness and integrity traits revealed a more coherent relationship with the default status in comparison to widely utilised demographic variables. Hence, across countries psychometric signs might be more trustworthy and decisive in estimating default probability.

Some traits measurable with psychometric tests have considerable link with repayment outcomes. Honesty and integrity evaluations have major role in human resources in evaluating unethical human behaviour (Klinger et al., 2013: 44). Hence, honesty evaluations could be instrumental in assessing willingness to repay. Psychometric tests, in addition contribute to evaluate repayment capability through money management, spending and saving attitudes, and money beliefs and behaviours. Lenders in emerging markets have limited available information about applicants and costs of underwriting process are high. Therefore, psychometric tests facilitate to examine characteristics of successful loan applicants.

The Entrepreneurial Finance Lab (EFL) is a company offering psychometric assessment tools in an innovative manner. EFL is partner of many banks and their tests are utilised as credit-screening tools in banks especially in the case of evaluating thin-fine applicants. Besides, applicants that are more likely to be rejected under the traditional underwriting process of banks can be evaluated by psychometric mechanisms in order to get more profit and perform decisions that are more accurate (Klinger et al., 2013: 98). EFL test was initially developed for evaluating SME entrepreneurs whether or not to grant credit. EFL initially integrated Big Five personality assessment, intelligence and integrity measures (Arráiz et al., 2015).

Arráiz, Bruhn and Stucchi (2015) studied the utilisation of psychometric tests of Entrepreneurial Finance Lab (EFL) to identify credit risks. Psychometric evaluation process eliminates information asymmetries and broaden the access to credit. EFL tool technically utilises personality traits for assessment of creditworthiness. Arráiz et al. (2015) implemented EFL test in Peru and explored that EFL test can be utilised as a secondary evaluation mechanism for identifying potential borrowers who are rejected under conventional underwriting process. Those individuals who have credit history are usually below the threshold level and by means of secondary evaluation they can be offered credit so as to increase profitability. In addition to this complementary role, psychometric tests can also be used for evaluating applicants that have no prior credit history. Study of the Arráiz et al. (2015) revealed evidence regarding the increase in credit access can be provided by using psychometric assessment in the case of information asymmetry.

1.5.5 Other Issues and Challenges

Technological developments and Big Data applications has shifted the applications of e-commerce to a wider platform, which enables financing and credit granting. Thus, e-commerce does not solely deal with money transfer anymore, it should also be supported by mechanisms capable of making credit transfer. These changes in the e-business environment require financial services' change as well especially in the case of credit risk assessment. Recently, e-finance includes a range of business activities comprising credit related tasks that dramatically affected the credit risk management systems. Even though banks offer online credit services nowadays, creditworthiness and credit granting decisions in most lenders depend on transaction data that is not dynamic (Han, 2007, as cited in Wang, Li and Lin, 2013). Online and real-time credit scoring is increasingly demanded in e-finance environment. This type of decision support systems are driven with the data, which is suitable for instant screening. For instance, transaction details may constitute a valuable sources of information for online scoring (Y. Wang et al., 2013).

In addition to transaction data from e-commerce platforms, social media data contributes to online and real-time scoring. Major advantages of utilisation of social media data are as follows: explores new customer segments having limited financial history, provides availability of numerous data points, assists in elimination of losses, facilitates cross check of information presented in the application process, aids in approaching new markets and customers, and improves risk based scoring and credit decisions (PWC, 2015, as cited in Ntwiga and Weke, 2016).

Blumenstock, Cadamuro and On (2015: 1073) pointed out that in contrast to developed countries where advanced data sources create opportunity for demographic profiling of credit applicants, in developing nations this kind of Big Data resources are limited. Demographic modelling through Social Networks and Internet of Things (IoT) are considerable data sources for developed nations. However, these sources are scarce in the case of developing countries and lack of 3rd parties involving in data analytics process constitute barrier in front of adoption of Big Data analytics based on social media or IoT data. In this case, mobile phone data can be utilised for knowledge discovery regarding the attributes of individuals as even in the poorest countries mobile phone utilisation rates are very high. Mobile phone data provide insight into consumption and expenditure patterns of individuals, their locations and travel preferences, and a wide range of wealth indicators.

However, there are some issues need to be addressed about information from social networks or from the resources mentioned previously. First of all, data from these resources may not be true and accurate. Thus, data from this kind of resources particularly social media data need to be crosschecked and combined with appropriate resources in the case of making credit decisions (Tounsi et al., 2017: 144)

Additionally, Guo et al. (2016) emphasised that solely using social media data or alternative data from online platforms can be problematic in the case of predicting default. Social media data and classification based on social media can be considered as an initial classification step in constructing final risk score. Assessment of some attributes from those platforms can cause false positive results, which necessitates combination with other features or verification from other resources. Moreover, personal characteristics can alter among cultures and it can be easy to manipulate social media profiles so as to achieve higher credit scores. Hence, social media data are viewed as a complementary resource in predicting default risk of individuals especially in the case of existence of limited financial data (Guo et al., 2016). Masyutin (2015: 16) draw attention on the scarcity of theoretical work about scoring based on network data. Because, history of the assessment of creditworthiness based on social network data depends no more than five years and mainly practitioners are not interested in dissemination of knowledge and experiences, due to operating in a very competitive environment. Thus, theoretical work in the area is limited.

Another concern is about the implementation of network-based data. Business processes should be adopted so as to support data driven decision making with the aid of robust data retrieval systems and data storage issues should be regarded carefully. Data retrieval can be conducted either in-house or outsourced. In addition, the legal framework about data processing is important. Depending on the fact that legal issues vary among countries, and the process should be regarded carefully for preventing penal sanctions (Masyutin, 2015: 16).

Lessmann et al. (2015: 3) draw attention to issues particularly associated with classification algorithms. Up-to-date advancements in credit scoring domain were indicated as follows; first, original classification algorithms for constructing models, original performance metrics to evaluate scorecards such as H-measure and Gini coefficient, and hypothesis testing for comparison of scorecard performance (Lessmann et al., 2015: 3). Lessmann et al. (2015: 3) indicated that these issues were not addressed by the relevant literature enough, and existing studies generally utilised few and/or small data sets, did not include comparative analysis with regard to classifiers and used merely a small number of conceptually very much alike accuracy indicators.

1.6 Overview of Credit Risk Models

Loan granting in finance sector is one of the most critical decision problems as decisions that are not right may result in distress of financial institutions and catastrophic impacts on economies which may require great governmental efforts for recovering the economy (Kabari and Nwachukwu, 2013: 8). Hence, managing credit risks properly by means of robust credit risk assessment models and decision support systems are critically important. Credit risk models depend on classification techniques utilised and generally, in the case of using a particular classification technique, no best technique applicable to all credit problems exists. Every problem has its own characteristics regarding the data structure, parameters used and the goal of the classification (Hand and Henley, 1997: 535).

Classification deals with allocating objects into previously defined categories. Classification models using a particular data set for input are constructed by means of classification techniques. This facilitates prediction based on historical data sets. Data mining in addition to education, information technology, medicine and biology, have been prevalently utilised in the field of finance. Credit scoring models were first introduced by Fisher (1936), and Altman (1968) contributed to the development of credit risk models (as cited in Dahiya, Handa and Singh, 2015: 165).

Credit risk models are used to compute a risk based score by means of particular methods and techniques. These methods can either be statistical models or artificial intelligence models or a combination of the two (Ntwiga and Weke, 2016). Implementation practices in the field differ based on the extent of accessible consumer data and relevant dynamics of the local consumer markets. For instance, Guseva and Rona-Tas (2001) investigated the difference of credit scoring systems in Russia and USA. Depending on the fact that market’s involvement of credit bureaus and maturity of the market are provided, quantification of risk assessment is possible in the case of USA. Contrarily, in Russia, which is an immature market, credit risk evaluation works differently. In this case, credit cards are allocated based on subjective assessments regarding the status of the social network, trust indicators, employment and family relationship bonds (as cited in Poon, 2007: 286).

Over the time performance of these models and models’ performance evaluation criteria have been the subject of a remarkable number of studies. One criticism about the performance of the models is that models using historical data cause wrong risk estimates, and model performance deteriorates over time as a result of regarding credit risk evaluation as a time independent matter (Ntwiga and Weke, 2016). Hence, psychological and behavioural factors have come into prominence so as to enhance existing models accuracy.

Based on the classification of Yu, Wang, Lai and Zhou (2008: 15392) techniques in decision support systems for credit scoring can be grouped into four categories; statistical techniques, operational research techniques, artificial intelligence techniques and hybrid / combined and ensemble methods. Statistical techniques comprise Discriminant Analysis, Logistic Regression, Probit Regression, K-Nearest Neighbour and Decision Trees. Linear Programming and Integer Programming can be considered within the Operations Research approaches. Neural Networks, Support Vector Machines, Genetic Algorithms and Case Based Reasoning are among Artificial Intelligence techniques.

In order to support complex credit decision problems, decision support systems within the field have adopted models employing statistical and artificial intelligence methods. Recently, attention of much research have been directed towards building ensemble systems depending on multiple classifiers. However, most of them concentrated on the models incorporating classifiers belong to the same algorithm. Further, incorporation of various classifiers that belong to diverse algorithms, and the way in which classifiers are combined have been the topic of a few studies (Ala’Raj and Abbod, 2016: 89).

1.7 Defining Credit Risk Models / Credit Scorecards

Decision making process in credit granting depends on statistical models known as credit scorecards or judgemental methods. Judgemental approach may consider character, condition, capital, capacity or collateral in the case of decision making. Decision making process in retail banking involves dealing with taking the right actions regarding the loan applicants. A database including descriptive characteristics and past behaviour associated with the domain is utilised to establish models capable of estimating future possible attitudes and behaviour. The prevalent word in consumer credit industry referring to these models is scorecard (Hand, 2005: 1109).

In a different way, scorecard is the name of the tool utilised in consumer lending industry with the purpose of evaluating credit applications. Scorecards have evolved over time from a basic paper box including statistical scores determined by the lender based on a set of answers to sophisticated software packages. Nowadays no paper scorecards exist as software packages, computer interfaces and electronic data warehouses serve for this purpose (Poon, 2007: 284). There were considerable differences in scorecards regarding their implementation and design issues. Depending on the fact that technology affected the risk estimation and changed architecture of the models and algorithms, application screening has undergone significant changes.

Scorecards or credit scoring decision models' output represents the category of the behaviour, which probably the applicant demonstrates. From this aspect, two class cases representing "good" and "bad" behaviour exist and scorecards behave like a map classifying applicants as good or bad. However, the class that a particular applicant belongs to cannot be determined properly all the time, which makes the requirement of the scorecard evaluation criteria more remarkable (Hand, 2005: 1109).

According to Masyutin (2015) a scorecard is formed up rules each of which assigns score points to the applicants. Those points are summed up to achieve an ultimate score. In order to classify good and bad loan status, decision boundary (cut off score) is compared with the final score of the applicant and decision is made accordingly (Masyutin, 2015: 19). Classically, default occurs after the 90 days of delinquency within the 12 months since the loan is committed according to retail banking (Masyutin, 2015: 17). Delinquent loans based on lenders' definitions and numerous past studies are characterised 90 days or more past due (Gardner and Mills, 1989: 56). Thus, final decision depends on a cut-off score previously determined based on lenders strategies and mostly scores of previous defaulters are utilised to adjust the cut-off score. Applicants having lower score than the cut-off are classified as bad, whereas those having scores over the cut-off are classified as good and are offered credit. In determining minimum acceptable risk degree, the cut-off score (threshold value) is critical. Based on Siddiqi’ s (2005) study, Kolmogrov Simirnov (K-S) statistics test can be used (as cited in Yap et al., 2011: 13280). The score producing the highest K-S test statistics can be taken into account as threshold value and minimum acceptable risk degree.

Credit scoring practices in USA are mostly carried out by the efforts of Fair Isaac Corporation (FICO Score) and the initial commercial product of the company was solely dependent on metrics from responses of applicants to a number of questions. This simple mechanism is called application scorecard (Poon, 2007: 289). Evolution of mechanisms went on by the developments in data repositories and data processing technologies, and between 1958 and 1974 application scorecards were mostly dependent on customized algorithms that are suitable for the particular lenders as a result of their varied customer portfolio. After 1970s, instead of customised products credit bureau data was taken into consideration and data from small institutions, lenders and banks were gathered to provide and consolidate data (Poon, 2007: 293).

Towards the end of 1970s first credit scoring system incorporating bureau data was developed which led the utilisation of new indicators in the evaluation process (Poon, 2007: 295). After the mid 1980s, instead of producing scorecards, FICO scores were developed and the business model of providing scores to the relevant businesses was utilisied by the Fair Isaac Company which provided to approach the risk management problem from a more unified perspective (Poon, 2007: 297). However, at this age the score is critized as it represents a limited part of a huge interconnected and complex mechanism. Depending on the prevelance of recent analytic tools and competitve forces (Poon, 2007: 301).

1.8 Predictive Modelling

1.8.1 Overview of Techniques Applied to Credit Risk Models

In general, credit scoring is a classification issue categorising loans as good or bad. Although this classification is technically based on the statistical models, seeking for more sophisticated techniques for classification that is compatible with the nature of the sample is vital in the way of accomplishment (Hsieh and Hung, 2010: 534). Table 1 represents the techniques that are mostly utilised in constructing credit scoring models.

Table 1
Classification Techniques

Linear Regression (LR)	Deep Learning (DL)
Discriminant Analysis (DA)	Support Vector Machines (SVM)
Weight-of-evidence Measure	Probit Analysis
Regression Analysis	Linear Programming
Cox’s Proportional Hazard Model	K-nearest Neighbour (K-NN)
Logistic Regression (LR)	Fuzzy Logic (FUZZY)
Decision Trees (DT)	Genetic Algorithms (GA)
Artificial Neural Networks (ANNs)	Bayesian Networks (BN)
Hybrid Methods	Ensemble Methods

Source: Tounsi, Hassouni and Anoun, 2017: 136; Abdou and Pointon, 2011: 68

According to Hand and Henley (1997), classification techniques can be classified as conventional and advanced techniques. Conventional techniques comprise of Linear Regression, Probit / Logit models and Discriminant Analysis, while Expert Systems, Genetic Algorithms, Fuzzy approach and Neural Networks are considered as advanced techniques in the field of classification (Hand and Henley, 1997, as cited in Abdou and Pointon, 2011: 67).

Parametric techniques and non-parametric or data mining techniques are utilised in the case of model construction. Parametric techniques include Linear Discriminant Analysis, Multivariate Adaptive Regression Splines (MARS) and Logistic Regression. Data mining methods often utilised to enhance accuracy of parametric techniques comprise of Support Vector Machines, Neural Networks, Genetic Programming, Artificial Immune System Algorithm, Case-Based Reasoning, K-Nearest Neighbour and Genetic Algorithm (Dahiya, Handa and Singh, 2015: 165).

Statistical credit scoring systems enhance decision making. In developing countries these models are highly necessitated in order to complement judgemental techniques depending on institutions' particular strategies (H. A. Abdou, Tsafack, Ntim and Baker, 2016). Statistical learning depending on statistics is an approach within machine learning and data mining constitutes a component of statistical learning. Both concepts can be interpreted as elements of a broader approach named Knowledge Discovery from Data (Cubiles-De-La-Vega et al., 2013: 6911).

Expert knowledge is also valuable in the credit scoring domain as expertise of decision makers or credit officers are built up by practising many cases and solving many decision problems over a long time period. However, heuristic character of expert knowledge makes the process of acquisition of expert knowledge challenging and burdensome. This issue is known as the knowledge acquisition bottleneck (Hoffman, 1987, as cited in Sinha and Zhao, 2008: 287)

Sinha and Zhao (2008: 287) stated that utilisation of data mining techniques in combination with expert knowledge have potential to complement formalizing the knowledge so as to support credit granting decisions.

Knowledge engineering refers to the process of constructing an expert system. A knowledge engineer extracting rules that are wise to follow, unwritten principles of behaviour and strategies from an expert associated with that particular domain facilitates the knowledge engineering process and a computer program is designed by using the heuristic knowledge of experts (Buchanan and Shortliffe, 1984; Waterman, 1986, as cited in Sinha and Zhao, 2008: 288).

Regarding the knowledge acquisition bottleneck Johnson (1983) stated that ability of experts in explaining their domain knowledge decreases by the competitiveness of the environment and methods including focus group studies, observational assessments, protocol analysis and interviews aid in capturing knowledge of experts (as cited in Sinha and Zhao, 2008: 288).

In general, when building a credit scoring model, analysis of the problem in detail, the structure of the data, parameters utilised, the goal of the classification and at what extent the classification is probable by using relevant parameters are all should be taken into account (H. Abdou, Pointon and El-Masry, 2008: 1278). Linear Discriminant Analysis and Logistic Regression were reported as the most widely used methods in credit scoring models (Baesens et al., 2003; Thomas, 1998, as cited in Šušteršič et al., 2009: 4736).

1.8.2 Machine Learning

Novel methods in scoring involve data mining. Data mining process includes the extraction of valuable patterns and rules among data. Data is analysed for obtaining useful information for strategic decision making and data mining approach facilitates this by providing knowledge discovery in databases (Yap et al., 2011: 13274). Data mining techniques have been implemented to areas of credit scoring, bankruptcy estimation and fraud detection. These techniques are composed of models, which deal with classification issues, and predictions are employed depending on past data and sample of similar cases (Sinha and Zhao, 2008: 287).

Data mining deals with anomaly detection, predictive modelling, association analysis and clustering (Yap et al., 2011: 13274). Anomaly detection considers anomalies like fraudulent cases, unusual diseases or events. Predictive modelling uses statistical models or machine learning to predict the outcome variable based on a set of input variables. Association analysis explores frequent occurrence of events together like items purchased together. Clustering deals with classification of objects into clusters demonstrating similar properties or behaviour (Yap et al., 2011: 13274). A wide range of statistical and machine learning techniques such as Decision Trees, Support Vector Machines, Logistic Regressions and Neural Networks have been utilised individually or in a combined manner to produce hybrid credit scoring models (Dahiya, Handa and Singh, 2015).

Machine Learning (ML) applies to a wide range of problems and it is powerful to improve the performance in credit risk assessments. Dealing with Big Data in the case of credit scoring has caused to be more concentrated on ML techniques. These methods can be categorized based on their learning types and subjective grouping, which deals with the thing that the model intends to accomplish. Learning types comprise of supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning (Tounsi et al., 2017: 135).

1.8.3 Advancements in Predictive Modelling

Supervised learning is utilised in predictive modelling and aims to construct model between output and selected input features according to historical data. Regression and classification are considered as the major supervised learning algorithms and the difference between the models is the output variable, which takes either continuous values or class labels (Tounsi et al., 2017: 135).

Comprehensive review of Lessmann et al. (2015) indicated that there are important advancements in predictive learning after 2003. Since then, in addition to individual classifiers homogenous ensemble and heterogeneous ensemble methods have been adopted by the relevant literature. Results of the studies comparing performance of these classifiers are complicated and reached contradictory findings in some cases. For instance, Logistic Regression demonstrated similar performance to some complex advanced methods and literature in the field is not sufficient to prove superiority of advanced classifiers. Sophisticated methods do not always enhance accuracy and additional evidence is required. Lessmann et al. (2015) stated that even though the dynamic ensembles are the most sophisticated novel techniques, performance metrics that they focused did not report higher level of accuracy than conventional alternatives such as Logistic Regression. Thus, complexity or advancements do not necessarily result in enhanced performance and accuracy of classifiers.

One comprehensive study regarding the classification algorithms in credit scoring domain is conducted by Baesens et al. (2003). Lessmann et al. (2015) conducted a systematic review of classification algorithms as well, so as to discuss more novel techniques and improve research gaps by reviewing the study of Baesens et al. (2003).

Lessmann et al. (2015) stated that in spite of a remarkable number of research literature there is lack of studies revealing recent improvements in the field of predictive learning. For instance, selective multiple classifier systems that combine different algorithms and conduct optimization on their weighting by means of heuristic search constitute a popular advancement in machine learning (Partalas et al., 2010, as cited in Lessmann et al., 2015: 3).

1.9 Techniques Applied to Credit Risk Models

1.9.1 Linear Regression

This type of regression has been widely used in credit scoring implementations in order to explore the relationship between the dependent variable and one or more independent variables. Linear Regression can be used for constructing factor scores and for comparing them with the decision makers' cut-off score for credit granting (Abdou and Pointon, 2011: 69).

Ordinary Linear Regression has been utilised in the field of credit scoring. Orgler (1970) used Linear Regression analysis for developing a credit scoring model for the assessment of the non-performing loans. As the past payment behaviour of customers were taken into account, constructed model was mostly behavioural and it was explored that behavioural variables had more predictive power rather that application data (as cited in Hand and Henley, 1997: 533). Sidoti and Devasagayam (2010) performed Linear Regression analysis as well.

Linear Regression is a common approach in credit scoring models. Lasso representation and elastic net are among extensions of Linear Regression. Lasso models offer agile algorithms in order to adjust linear models with elastic net penalty (Friedman et al., 2010, as cited in Addo et al., 2018: 3). Hence, this method is found appropriate when dealing with large datasets.

In addition to Linear Regression, regression models can be classified as logistic or multinominal regression. The goal is to perform predictions with lowering prediction errors. The response has binary outcomes (0 or 1) in the case of Logistic Regression and conditional probabilities are demonstrated by means of a nonlinear function of the input variables. Regarding the Multinominal Regression the response has more than two possibilities and the function of the conditional probabilities are computed accordingly (Addo et al., 2018: 4).

1.9.2 Logistic Regression

"Regression estimates dichotomous outcomes" and does not necessitate multivariate normality assumption (Šušteršič et al., 2009: 4736).

Similar to Discriminant Analysis, Logistic Regression's usage is widespread in building models for credit scoring. The difference of Logistic Regression from Discriminant Analysis is the dependent variable, which is dichotomous in the case of Logistic Regression (Yap et al., 2011; H. A. Abdou and Pointon, 2011: 71).

Theoretical studies proved better performance of Logistic Regression compared to Linear Regression in the case of credit scoring. Wiginton (1980) was one of the first studies applied Logistic Regression in credit scoring domain and explored good classification findings (as cited in Hand and Henley, 1997: 533). In spite of the existence of advanced statistical techniques, credit scoring in banking and finance institutions often uses Logistic Regression and Decision Trees for their practicability. These methods are found relatively clear to explore the important input characteristics, to anticipate the findings and to construct the models (Yap et al., 2011: 13275).

Yap et al. (2011) developed credit scorecards based on Logistic Regression and Decision Trees. Ganzach and Amar (2017) predicted debt repayment difficulty based on Logistic Regression model by examining a sample drawn from general population in U.S. Rogers, Rogers and Securato (2015) employed the approach of Logistic Regression for developing probability of default model that integrates various facets of creditworthiness. Akben-Selcuk (2015) utilised Logistic Regressions. Nyhus and Webley (2001) constructed a Logistic Regression model for evaluation of positive financial behaviour. Davies and Lea (1995) employed Logistic Regression to discriminate debtors from non-debtors.

von Stumm et al. (2013) proposed a model for predicting financial behaviour based on Logistic Regression. Perry (2008) investigated the influence of personality in credit ratings by constructing a model for estimating determinants of actual credit scores. FICO scores of participants were taken into account to construct a Logistic Regression Model. Stone and Maury (2006) suggested a Logistic Regression model for representing multi-disciplinary behaviour.

Yap et al. (2011: 13276) proposed credit scoring models which were constructed by SAS Enterprise Miner 5.3. Logistic Regression and Decision Trees model were utilised to classify loan borrowers. Data comprised of defaulters (35%) and non-defaulters (65%). Utilised software included a credit scoring model as well, which was implemented by researchers in addition to Logistic Regression and Decision Trees. Classification in this approach is conducted by the Interactive Grouping node, which automatically chooses and categorizes variables by utilising the metrics of Weights of Evidence (WOE) and Information Value (IV). The WOE of a variable refers to the logarithm of the proportion of "goods" to "bads" associated with the particular attribute. After classification, IV metric assists to estimate the separation ability or estimation power of the variable regarding the high and low risk applicants. IV value bigger than 0.02 was taken into account for parameters to be included in the credit scorecard (Yap et al., 2011: 13277). Yap et al. (2011: 13277) stated that variables having an Information Value over 0.02 were taken into account for model development.

Huo, Chen and Chen (2017: 247) incorporated Logistic Regression model with Back Propagation Neural Network for accuracy improvement in classification. Output of the Back-Propagation Neural Network model was considered as a new extensive variable inputted to Logistic Regression model. Contribution of parameters were selected based on Weight of Evidence (WOE) metrics. The Information Value of parameters were determined by means of weighted sum of Weight of Evidence values. The variables representing greater Information Value were as follows: online & offline durations, times of overdue payments, amount of overdue payments, online duration and number of days of communication. Predictive accuracy of the combined models was higher than the LR model.

Gardner and Mills (1989: 59) first examined hypothesized relationships among variables by non-parametric and univariate tests. Chi-Square test was utilised for examining the relationship between dependent variable and other categorical variables. Hereafter, Logistic Regression was utilised to investigate simultaneous impact of the variables on the probability of default. Hancock et al. (2013) used Logistics Regression for predicting problematic debt credit behaviour and debt levels. J. Wang and Xiao (2009: 2) constructed a model based on Logistic Regression in order to predict indebtedness. Godwin (1999) predicted repayment difficulty based on Logistic Regression. Rutherford and Devaney (2009) applied Logistic Regression analysis for predicting credit misuse of American households.

Chien and Devaney (2001) utilised Stepwise Regression to determine factors having significant contribution on prediction of outstanding credit. This procedure was used as an automatic search mechanism, which offers the best set of indicators. Factors represented 0.15 and above significance levels were included in the prediction models. After application the stepwise procedure, Ordered Logistic Regression analysis was performed.

1.9.3 Other Types of Regressions

Yilmazer and DeVaney (2005) applied Multiple Regression Analysis on secondary data of American households. Norvilitis et al. (2006) applied Multiple Regression Analysis for predicting antecedents of level of debt among college students. Norvilitis and MacLean (2010) applied Multiple Regression Analysis on data of college students in U.S. Chen and Wiederspan (2014: 576) utilised Zero-one inflated Beta Regression for examination of determinants of debt levels. This type of regression was preferred as the dependent variable of the study was ratio / proportional including zero values. This type of regression adjusts the data by means of maximum likelihood estimation (MLE) techniques.

Meng, Hoang and Siriwardana (2013: 80) utilised a Cointegrated Vector Autoregression (CVAR) model for discovering antecedents of debt among Australian sample. Gray (1985) constructed probability of default model based on Multiple Logistic Regression analysis. Bernerth, Taylor, Walker and Whitman (2012) proposed a credit risk evaluation system based on Multiple Regression Analysis. L. Wang, Lu and Malhotra (2011) used Stepwise Regression Analysis to predict outstanding debt levels. Nepomuceno and Laroche (2015) employed Hierarchical Regression Analysis as well. L. Wang, Lv and Jiang (2011) used Stepwise Regression analysis for model of debt repayment behaviour. Strömbäck et al. (2017) and Brougham et al. (2011) utilised Ordinary Least Squares (OLS) Regressions.

Donnelly, Iyer and Howell (2012) employed Two-Step Hierarchical Regression analysis for two separate studies for determining factors causing responsible financial behaviour and debt accumulation. Ordered Logit Regression analysis was performed by Lea et al. (1995) for predicting level of debt.

Logistic Regression and Linear Discriminant Analysis are widely accepted and strong method for credit scoring models. Depending on the fact that they produce linear scorecard for evaluating creditworthiness nonlinear machine learning techniques that are capable of dealing with nonlinear relationships were proposed. Hence, combination optimization of more than one methods has emerged as an advancement in the field of decision support systems for credit scoring (Huo, Chen and Chen, 2017: 245).

1.9.4 Discriminant Analysis

Depending on the fact that Discriminant Analysis is a kind of parametric analysis technique used for classifying different groups, a great number of researchers accepted Discriminant Analysis as one of the most prevalent technique, which is still in use for discriminating good and bad loans. Probably one of the earliest utilisation of the multiple Discriminant Analysis was the study of Durand (1941) (as cited in H. A. Abdou and Pointon, 2011: 69). Since then Discriminant Analysis technique has been used by many researchers for the purpose of building credit scoring models.

Discriminant Analysis is considered as a practical and convenient method for categorising groups according to chosen characteristics. Linear Discriminant Analysis depends on the linear aggregation of predictor variables (Cubiles-De-La-Vega et al., 2013: 6912), and the technique facilitates to observe the impact of independent variables on the dependent variable in a simultaneous manner (Ryan, 1993: 33).

Since the Durand's (1941) study proved accurate results for scoring by using Discriminant Analysis, the method has been criticized because of its critical assumptions such as normal distribution of the variables representing the group members under assessment (as cited in Hand and Henley, 1997: 532). Regarding the Linear Discriminant Analysis Šušteršič et al. (2009: 4736) reported that it is a limited analysis technique in terms of assuming linear relationship between variables while they are mostly nonlinear and necessitates multivariate normality assumption.

However, a substantial amount of studies reported credit risk models based on Discriminant Analysis. Ryan (1993: 33) estimated probability of default of students based on Discriminant Analysis. Chi-Square statistics was utilised for selecting statistically significant features and determining variables to be included in the Discriminant

Analysis. Tokunaga (1993) utilised Discriminant Analysis as well, for the purpose of predicting credit misuse. Wilms, Moore and Bolus (1987) estimated probability of default on educational loans based on Discriminant Analysis. Livingstone and Lunt (1992) utilised Multiple Regression Analysis and Discriminant Analysis to explore factors causing outstanding debt. At first discriminant function analysis was utilised to explore debtors and then Multiple Regression analysis was employed to discover at what extent they were in debt and at what extent they made regular repayments.

Alternative to Discriminant Analysis, Tobit Analysis was used by some researchers for estimating probability of default (Greene, 1989). Greene (1989: 61) stated that Tobit models were superior to Discriminant Analysis, as a result of not only examining the categorical status of the dependent variable.

1.9.5 Probit Analysis

Probit Analysis is considered as a traditional technique in credit scoring era. This technique focuses on determining coefficient values and a linear combination of independent variables is converted to its cumulative probability (Abdou and Pointon, 2011: 70). L. Wang, Malhotra and Lu (2014) used Linear Regression and Probit Regression Analysis for estimating customers with problematic debt levels. Employing Probit Regression Analysis, Ottaviani and Vandone (2011) estimated level of debt as well.

1.9.6 Decision Trees

Decision Tree refers to a decision support mechanism which utilises a tree similar graph or model for decisions and their probable outcomes (Kabari and Nwachukwu, 2013: 9). Graphical tools are utilised in the construction of Decision Trees and the node is represented in a box having lines to signify probable events and their results till the optimal solution is achieved (Ala'Raj and Abbod, 2016: 95).

Decision Trees are among the most prevalent techniques utilised for classification and prediction purposes in machine learning approaches. The Decision Tree approach can both handle numerical and categorical data, which is appropriate for credit scoring domain. Decision Tree resembles an inverted tree with branches and internal nodes. Nodes depict a test regarding a variable while branches demonstrate the result of the tests.

Each terminal node has a class label and it is easy to transfer the tree structure to the classification rules, which is not a complex and burdensome process (Zhang et al., 2016). Decision Tree or Recursive Partitioning have been performed in numerous disciplines (Hand and Henley, 1997: 534). As a result of demonstrating well performance in classification, Decision Tree algorithms are applied to a wide range of problems in medicine, biology, finance and manufacturing (Han, 2012, as cited in Zhang et al., 2016: 170). Especially in operations research, the optimum way to achieve a goal is determined through decision analysis by employing Decision Trees. Conditional probabilities can also be estimated by utilisation of Decision Trees (Kabari and Nwachukwu, 2013: 9).

A number of Decision Tree algorithms exist and the difference between them stems from the way how the tree is constructed. Iterative Dichotomiser (ID3) algorithm uses a top-down recursive approach in the case of tree establishment and so as to provide a simple classification tree the metric of information gain is utilised for attribute selection process (Quinlan, 1986, as cited in Zhang et al., 2016: 170). Both C4.5 and C5 algorithms are improved versions of ID3 with the properties of dealing with both continuous and discrete variables (Zhang et al., 2016: 171).

The Decision Tree initiates with a root node and constructs sub-trees including internal nodes. Each internal node means a test of an attribute while each branch demonstrates a binary partition of the test feature. The steps for constructing a Decision Tree follows divide and conquer approach applied as follows; root node accounts for the overall test data and each node split accounts for a partitioning of the data of that node according to the test condition for the relevant feature. Thus, there are two main issues associated with the Decision Tree construction; the way how the split attribute is selected and the number of levels that each tree branch includes. Random Forests approach formed up a set of Decision Trees performs the splitting based on Gini Index (Breiman, 2001, as cited in Malekipirbazari and Aksakalli, 2015: 4627).

Decision Tree model includes rules for splitting the observations into smaller groups with regard to a specific target variable. Target variable is often categorical and the Decision Trees can be utilised to estimate the probability of falling into each target category for a specific record, or to determine the record's category (Yap et al., 2011: 13277). Chi-square automatic interaction detector (CHAID), classification and regression tree

(CART) algorithms are among the other prevalent types of Decision Trees (Yap et al., 2011: 13278)

Kabari and Nwachukwu (2013: 12-17) proposed decision support system incorporating Decision Trees and Neural Networks techniques, for supporting loan granting decisions by using a set of financial, socioeconomic and demographical variables such as income, job experience, residential status, place of employment and social security. This hybrid model demonstrated 88% prediction accuracy for loan granting. Researchers combined the two model for their complementary nature. For instance, interpretation of Neural Networks is complicated and its learning process might take time, which is not true for Decision Trees. On the other hand, Neural Networks are not capable of dealing with noise in the case of training opposed to Decision Trees.

1.9.7 Random Forests

Within the Decision Tree context, in some applications for providing accuracy enhancement ensemble techniques including boosting and bagging can be utilized. Random Forests (RF), that considered as an advanced bagging method, is a robust method in building Random Forests based Decision Trees. RFs establish numerous Decision Trees on bootstrapped training data. Nevertheless, in the case of constructing trees candidate split features are selected by means of random choose of a number of attributes from the whole set of attributes. The split can solely utilise the selected attributes and new attributes are selected in each split (Malekipirbazari and Aksakalli, 2015: 4627).

Random Forest modelling was first introduced by Breiman in order to establish an ensemble model based on a number of Decision Trees (Breiman, 2000, as cited in Addo et al., 2018: 4). Random Forest based classifier is formed up a set of tree-structured classifiers rN(x, βk), k = 1, ... where the βk represent random variables utilised in the case of construction of Decision Trees. Thus, efficiency of Random Forests rely on the tree-structured classifiers and the dependence among them (Addo et al., 2018: 4).

Malekipirbazari and Aksakalli (2015) studied on Random Forests (RF) based classification for predicting probability of default on borrowers of a social lending platform. Results were compared with actual FICO credit scores of borrowers and findings revealed that RF had better performance than FICO scores in classifying good and bad borrowers. In addition to Random Forests, Support Vector Machines, Logistic Regressions and K-nearest Neighbour algorithms were tested for their performances. RF based approach demonstrated better performance than the other machine learning methods. (Malekipirbazari and Aksakalli, 2015). Björkegren and Grissen (2018: 68-70) proposed a model for digital credit based on Random Forests approach as well. Constructed model was compared with traditional credit scoring approach using Logistic Regression. Random Forests performed better with mobile phone data than credit bureau data. Researchers proved that for individuals lack of financial history or credit bureau data, traditional scoring performed poorly.

1.9.8 Expert Systems

In addition to data mining approaches to credit granting decisions, in many application areas human experts' knowledge or systems with models depending on the decision making process of human experts are utilised. Hand and Henley (1997: 534) draw attention to one of the most superiority of Expert Systems applications. In practice, giving proper explanations to the applicants for declining their application is extremely important and considered as a legal requirement in many countries. Expert Systems facilitate to explain the rationale behind rejecting applicants as information on decision procedure is accountable. Utilisation of Expert Systems have been in rise for the last two decades. These systems are easy to apply and they do not necessitate very sophisticated mathematical models (Odeh et al., 2011: 8851).

Expert System refers to a computer-based information system, which utilises Artificial Intelligence approaches. Entire types of Expert Systems necessitate knowledge to function. Three major categories of knowledge exist including declarative, meta-knowledge and procedural (Turban et al., 2005, as cited in Miah and Genemo, 2016: 2). Declarative knowledge comprises facts and realities and usually represented as an easily understandable expressions. Difference of declarative knowledge and procedural knowledge stems from their utilisation. Declarative knowledge is used throughout the Expert Systems' development phase and is communicated by experts in the form of facts. However, procedural knowledge necessitates information about how the things are done (Jaques et al., 2013). Figure 1 depicts the major components of a functioning Expert System.

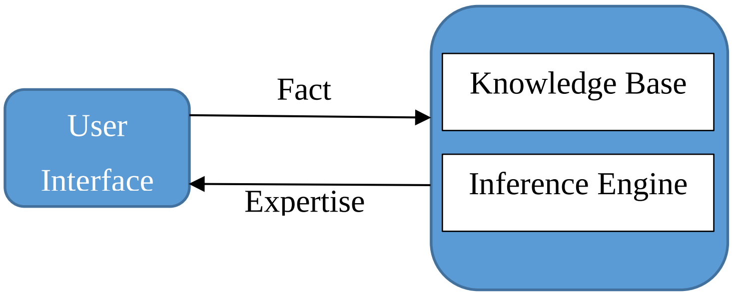

Figure 1: Major Expert System Elements

Source: Miah and Genemo (2016)

Sinha and Zhao (2008: 287) proposed a decision support system integrating a set of data mining techniques and knowledge based Expert System in order to achieve a high level of system performance. They utilised data mining techniques in combination with expert knowledge and compared this model with the model solely incorporating data mining techniques. Models' performances were compared by the metrics of misclassification cost and Area Under Curve (AUC). Rationale of researchers behind utilisation of an Expert System approach and data mining together is their complementary nature. From the viewpoint of knowledge engineering, major concentration is on the knowledge while data mining deals with the data, which makes them complementary in nature if both of them exit within the organization (Sinha and Zhao, 2008: 288).

For expert model construction a set of structured and unstructured interviews were conducted to exploit domain knowledge and rules were extracted. Regarding the classification algorithms Naïve Bayes, Logistic Regression, Decision Trees, Neural Networks, KNN and Support Vector Machines were utilised (Sinha and Zhao, 2008: 290). Expert models were used to analyse applicant's credit score from credit bureau and this output was used as an input for the data mining techniques. Partial domain knowledge regarding the credit bureau parameters was incorporated to the models utilising data mining methods. Results of the study proved significantly better performance by demonstrating lower misclassification costs (Sinha and Zhao, 2008: 291). Dybowski et al. (2003) stated that when both data and expert knowledge exist in a particular domain, it is valuable to utilise both of them in combination to get better insight into the associated problem (as cited in Sinha and Zhao, 2008: 291).

1.9.9 Neural Networks

Neural nets approach aims to construct nets, which are similar to human brain. These nets are established by components acting like human brain. Similar to the structure and working mechanism of the brain, each component within the net receives a set of inputs to produce a single output. Hence, Neural Network can be defined as a system, which receives inputs and performs calculations and operations to generate an output (H. Abdou et al., 2008: 1279).

Kabari and Nwachukwu (2013: 10) mentioned limited explanation capability of Neural Networks, which is also known as black box characteristics. Due to these characteristics, Neural Networks' penetration for practical industrial cases is relatively slow. Its performance fulfils its potential when it is combined with other machine learning techniques. Neural Networks application for credit scoring takes place by sending attributes of the borrowers to the input layer. After being processed, data is transmitted to the hidden layer for additional processing. Estimated values received by the output layer provides the ultimate result for the decision problems regarding the loan granting (Ala'Raj and Abbod 2016: 94).

Every Neural Network system is constructed by a set of interconnected and interactive processing components, which are similar to neuro-biological models. The major properties of these networks are the processing components and the learning mechanism utilised to discover weights. Weights are set by means of training dataset including data having recognized inputs and outputs (Šušteršič et al., 2009: 4738).

In detail, Neural Networks are established by forming layers. Major components of those systems are simple "nodes" or "neurons" which are linked through a single layer or multiple layer system. Number of nodes in neural nets alters based on the type of the system that is utilised. Every node or neuron executes a basic computation by using some inputs to achieve an output. Output produced by one neuron is then used by another neuron (Irwin, Warwick and Hunt, 1995; Palisade, 2005, as cited in H. Abdou et al., 2008: 1279). The process of setting the weights for providing the Neural Network to learn the relationship between the input values and the target value is known as learning or training. This learning mechanism can be supervised or unsupervised learning. For supervised learning, inputs and target data are given for whole objects. After each object, weights are redefined and the output is checked against actual target. Every iterative stage's, also called "epoch" networks', answers are checked against target values in the training dataset and total error of one iterative step is recorded. This process goes on until the predefined acceptable mean square error (MSE) is obtained. The major difference of unsupervised learning from supervised learning is the training dataset, which does not include target values. Thus, this type of learning is applied to problems associated with discovery of features of data, for instance clustering issues. One layer Kohonen Aritificial Neural Network (ANN) is an example for unsupervised ANN, and it was stated that it is good at for dealing with grouping and classification problems (Zupan and Gasteiger, 1993, as cited in Šušteršič et al., 2009: 4738).

Neural Networks can be either feedforward or recurrent. Feedforward networks include input and output layer and hidden layers. Backpropagation is the most prevalently implemented algorithm and its learning mechanism is employed through a network with established weights and interconnections. Gradient descent is utilised for decreasing the squared error between the actual and the desired output (Kabari and Nwachukwu, 2013: 13).

1.9.9.1 Probabilistic Neural Nets

Multi-layered feed-forward net comprising four layers and application of the kernel Discriminant Analysis functioning among those layers is called Probabilistic Neural Net. When a Probabilistic Neural Net is subject to a case, each node of the first layer computes the distance between the input incidence and the output incidence. Calculated value pass to the second layer and every node aggregates the output values from the nodes associated with the training cases. Those output values can be anticipated as probability function estimates of each class. Consequently, predicted category is defined by means of choosing the category having the highest probability function value (H. Abdou et al., 2008: 1280).

1.9.9.2 Multi-Layer Feed-Forward Nets (Multi-Layer Perceptron Networks)

When the relationship among variables is complex, utilisation of this type of neural nets is considered appropriate. This type of Neural Network is the most widely utilised architecture (Cubiles-De-La-Vega et al., 2013: 6913). The output of a particular layer can be defined as a connection-weighted aggregation of outputs passed from former layer.

Sigmoid function, which can be utilised in Logistic Regression as well, can be used in neural nets. Characteristics specific to multi-layer feed-forward neural nets are their capability of achieving results by the use of a small set of training data, compact size and having high performance in classifying. However, when compared with probabilistic neural nets they have some limitations as probabilistic neural nets produce results faster, they do not necessitate hidden layers and nodes, they have ability of estimating probabilities for different dependent values and assure converging to an optimum result (Palisade, 2005, as cited in H. Abdou et al., 2008: 1281).

Blanco et al. (2013: 356) studied on a decision support system for credit scoring in micro finance institutions. Model was build using Multilayer Perceptron Approach (MLP) and its performance was compared with Logistic Regression and Discriminant Analysis. Neural Network model's performance was superior to other models. Logistic Regression model's performance was better than two types of Discriminant Analysis. However, when models compared with MLP, these MLP models outweighed the performance of Logistic Regression and Discriminant Analysis.

H. Abdou et al. (2008: 1275) used Neural Networks and conventional techniques comprising Discriminant Analysis, Probit Analysis and Logistic Regression in order to analyse and compare their capability in terms of predicting loan default. Findings of their study demonstrated better results for Neural Networks with a higher average correct classification rate. Šušteršič et al. (2009) proposed a credit scoring system using error back-propagation artificial Neural Networks and compared its performance with regard to Logistic Regression. The problem and the dataset they used were well suited to the utilisation of the Neural Networks, which produced better results compared to Logistic Regression. However, Neural Networks' training process is long and after the establishment optimum network structure, the model behaves as a "black box" and it is difficult to determine significance of potential input parameters (Šušteršič et al., 2009: 4737).

1.9.9.3 Deep Learning

History of Neural Networks depends earlier times as first attempts of supervised Neural Networks were derived from Linear Regression. At late 1960s, the concept of learning and the approach of Neural Networks having a set of non-linear layers were emerged, and after 1990s researches on deep learning were introduced. Practical applications of deep learning became possible after advancements in unsupervised learning from the beginning of 2000s. Deep learning approach incorporates additional layers into neural nets and may use one of the following strategies in case of constructing the architecture: convolutional, recurrent, recursive or standard deep neural nets (Addo, Guegan and Hassani, 2018: 6).

1.9.10 Genetic Algorithms

Genetic Algorithm (GA) is accepted as an effective optimization technique, which depends on the idea of biological evaluation (Šušteršič et al., 2009: 4737). First of all, whole probable answers or solutions of a particular problem are introduced, and the process goes on by generation of a set of new generations including various answers with the aim of discovering better solutions. This GA process basically depends on four steps including generation of the population, assessment, selection and regeneration and till the identification of a possible improvement the procedure continues by repeating the last three steps of the GA. The evaluation of the candidate solutions are assessed by means of fitness function, which evaluates at what extent the solutions provide solution to the particular problem. The output of this function is utilised for identifying the set of solutions as “parents” for the generation of the population. Throughout the reproduction step, totally a new list of solutions for the population is explored by means of implementing genetic operators (Šušteršič et al., 2009: 4738).

Odeh et al. (2011: 8850) stated that credit decision problem often requires more than one issue to be solved. Depending on the fact that traditional optimization mechanisms are limited in dealing complex decision problems, Odeh et al. (2011) implemented Fuzzy Simplex Genetic Algorithm in producing decision rules in order to estimate probability of default.

1.9.11 Support Vector Machines

Support Vector Machines (SVM) based techniques focus on to lower the upper bound of the generalization error instead of the empirical error. Regarding the learning process, training step necessitates addressing a quadratic programming problem. One limitation is the possibility of facing with a large scale quadratic programming issue which makes the computing complicated. Hence, some algorithms have been utilised to eliminate the complexity. For instance, the sequential minimal optimization algorithm depends on the idea of dividing a large scale quadratic programming problem into smaller problems for approaching the problem in an analytical manner. Hence, the performance of the SVM is highly dependent on the algorithm used for addressing the problem. Another important issue to be taken into account is the setting of the parameters which influences the model's performance (Yu, Yao, Wang and Lai, 2011: 15393).

Support Vector Machines approach is considered as an efficient mechanism in the case of decision support systems for credit risk assessment. Nevertheless, SVMs' performance is impressionable to algorithm for clarifying the quadratic programming and adjustment of parameters regarding its learning instrument (Yu et al., 2011: 15392). Yu et al. (2011) proposed a model based on weighted least squares SVM for credit risk assessment decision support system which employs least square algorithm for dealing with quadratic programming problem.

1.9.12 Smoothing Non Parametric Methods (Nearest Neighbour Methods)

Nearest Neighbour Methods' first implementations worked on a loan portfolio of bank in New York and classification is provided by means of relative amount of loans with identical characteristics vectors. These methods have some advantages for applications in credit scoring. For instance, when the class of an applicant is known, the design set can be renewed easily by including the applicant or excluding the older situations. In spite of this practicality, researchers or practitioners due to computational requirements have not used these methods widely (Hand and Henley, 1997: 535).

1.9.13 Naïve Bayes

Naïve Bayes are statistical classifiers that classify given data into categories, which depend on Bayesian theory (Ala'Raj and Abbod, 2016: 95).

1.9.14 Mathematical Programming

Mathematical programming approaches such as linear programming or integer programming can also be applied to credit scoring problems. In the case of mathematical programming, deterministic relationships between variables are not problematic which makes the aproach advantageous (Hand and Henley, 1997)

1.9.15 Hybrid and Ensemble Classifiers

Traditionally, classification is often based on a single classifier or combination of a few classifiers, which can lead some deficiencies in characterising the samples. In order to overcome this issue, the idea of ensemble classifiers is proposed. Ensemble classifiers are constructed by combining various types of classifiers or dissimilar instantiations of a particular classifier so as to produce an ultimate classification decision. Hence, this ensemble classifiers are capable of dealing with different sample properties by means of classifiers meeting special requirements (Hsieh and Hung, 2010: 534). Therefore, some credit scoring research has focused on the performance improvement in credit risk models by applying ensemble methods.

Ensemble learning is an advanced machine learning technique which includes multiple classifier system comprising independently trained classifiers (Kittler et al., 1998, as cited in Dahiya et al., 2015: 165). In using classification algorithms, classification can be conducted as individual or hybrid manner, or a set of base classifiers can be combined to apply ensemble approach. Individual classification depends on a specific classification algorithm whereas ensemble method combines various classifiers for performance improvement with appropriate weighting (Dahiya et al., 2015: 166).

Data sets utilised for building credit scoring models have different characteristics. Depending on the fact that using a single base classifier may not be capable of handling various relationships among datasets, hybrid approaches are used for complementing individual classifiers and provide a robust learning mechanism. Ensemble models considered within the hybrid modelling approach use novel methods for learning on different segments of data and features. Ensemble approach employs independent training for all individual classifiers and their decisions are integrated by means of an algorithm to form the ultimate decision (Zang et al., 2014, as cited in Ala’Raj and Abbod, 2016).

The difference among hybrid and ensemble techniques is that hybrid models depend on a single classifier in the case of learning and implement feature selection and classifying processes in another way, whereas ensemble models apply numerous classifiers and different variables and training process is conducted with differing samples (Dahiya et al., 2015: 166).

Homogeneous and heterogeneous ensemble models refer to the combination of the same or different algorithms, respectively. Mostly studies performed so far, utilised homogeneous ensemble approach with basic combination strategies like majority voting, fuzzy rules, reliability based methods, weighted average, stacking or weighting vote (Ala'Raj and Abbod, 2016: 90). Classifier consensus approach is a novel combination technique depending on the decision making process of a group of experts. First decisions of base classifiers are shared, and until reaching to a consensus regarding the optimal ultimate decision the communication process goes on. Hence, this methodology is accepted as a novel combination technique, which provides efficiency in decision making (Ala'Raj and Abbod, 2016: 90).

Ala'Raj and Abbod (2016: 92) reviewed studies on the ensemble classifiers. A high percentage of studies utilised more than one datasets and applied homogeneous approach to ensemble learning. Except a few studies, most of them used majority vote method as combination strategy.

1.10 Literature Findings 1_Classification Techniques

Ju and Sohn (2014: 119) indicated that existing credit scoring models have the limitation of dealing with historical data and predefined attributes associated with this data. However, trends and technological changes necessitate alteration of these variables and bring updating requirements. Therefore, they suggested a technology credit scoring model, which is capable of updating available attribute set. The rationale behind the approach was developing scenarios to explore new parameters from their potential link with existing parameters. Exploratory Factor Analysis (EFA) was utilised in order to eliminate multi-collinearity in new parameters, and Logistic Regression was used for discovering the ultimate set of parameters for the credit scoring model. Finally, Analysis of Variance (ANOVA) was contributed to comparatively analyse the performance of resulting credit scoring models that were established based on the different scenarios about the association among existing and ultimate parameters. Optimum scenario was determined based on ANOVA, which demonstrated prediction accuracy (Ju and Sohn, 2014: 119).

“In conventional statistical classification techniques, an underlying probability model was assumed to calculate the posterior probability upon which the classification decision made” (Hsieh and Hung, 2010: 538). In order to overcome such limitations Neural Networks and Support Vector Machines have been utilised by researchers. Neural Networks was first used in 1990s, and Support Vector Machines’ utilisation was proposed by Vapnik (1995) (as cited in Hsieh and Hung, 2010: 539). Credit scoring systems for the purpose of decision making and risk estimation have been widely adopted in developed countries. Depending on the fact that research on developing countries is limited, H. A. Abdou et al. (2016) proposed a knowledge-based decision support system for credit scoring in Cameroon. Based on Neural Networks, Logistic Regression and Classification and Regression Trees, models were developed and their performances were compared with Receiver Operating Characteristic (ROC) curves and Gini measure. Prediction performance of Cascade Correlation Neural Network was superior than the other models’ performance. Bayesian Networks method was also suggested by researchers for their ability in modelling complex relationships and coping with missing data problems in credit scoring (Hsieh and Hung, 2010: 539).

Louzada, Ara and Fernandes (2016) conducted a systematic review on techniques utilised for credit risk assessment. The findings demonstrated how classification techniques used for this purpose evolved throughout years. Lessmann et al. (2015) conducted a systematic review as well. However, they did not take into account general methodological nature of classification algorithms. Because there are a wide range of approaches applicable to classification and a considerable number of them are modifications of each other (as cited in Louzada et al., 2016: 3). Louzada et al. (2016: 1) therefore performed a more overall systematic review on the classification techniques employed in credit scoring. Research period included studies between 1992 and 2015, which was divided into 4 periods for observation.

H. A. Abdou and Pointon (2011) conducted a comprehensive review regarding the credit scoring models and techniques, and how they evolved over time. They both reviewed various statistical methods and performance assessment metrics utilised for this purpose. Depending on the fact that decision making process varies among different institutions based on the different circumstances, no single solution exists for the credit risk assessment domain.

Louzada et al. (2016: 1) mentioned Neural Networks, Support Vector Machines, Linear Regression, Decision Trees, Logistic Regression, Fuzzy Logic (FUZZY), Genetic Programming, Discriminant Analysis, Bayesian Networks, Hybrid Methods (HYBRID) and Ensemble Methods (ENSEMBLE) as the classification techniques in reviewed papers. Overall findings indicated that Neural Networks and Support Vector Machines were the most widely used individual classifiers. Logistic Regression was mostly utilised recently and caught up the percentage of Neural Networks (15.2%). Moreover, there was a sharp decrease in the utilisation of Discriminant Analysis, Fuzzy Logic and Genetic Algorithms while the utilisation of combined techniques demonstrated significant increase after 2010. Hybrid methods' utilisation have not evolved over the different time periods and mostly used in papers having the goal of suggesting a new credit scoring model. Specific to studies having the goal of comparing different algorithms, Logistic Regression was the most prevalent technique in all time periods.

More than half of the reviewed papers aimed to propose a new method for credit scoring and almost 20% of them compared novel algorithms with traditional techniques. Nearly 15% of papers involved conceptual discussion. Literature review, performance measures and feature selection were topics of limited studies. Ensemble methods refer to incorporating classifiers and some proposed ensemble approaches as bagging, boosting and stacking (Breiman, 1996; Schapire, 1990; Wolpert, 1992, as cited in Louzada et al., 2016: 10) and Hybrid methods can be classified as a specific type of stacking (Louzada et al., 2016: 10).

Garcia, Marques and Sanchez (2015) focused on methodological issues in decision support systems for credit scoring. Hence, a systematic review was conducted to discover some patterns and make conclusions with papers in credit scoring and bankruptcy estimation implementations. Previously, Abdou and Pointon (2011) focused on the important aspect of credit scoring models and mentioned the critical factors in model development. Sadastrasoul et al. (2013) studied the evolution of data mining techniques applied to credit scoring (as cited in Garcia et al., 2015: 160). Contrast to existing reviews such as summarizing statistical and machine learning methods, Garcia et al., (2015: 160) concentrated on the experimental design issues in the associated domain. It is therefore, aimed to examine experimental data, data splitting techniques, criteria for performance assessment and significance tests. According to findings some drawn conclusions were as follows: most papers had small sample sizes, a remarkable number of studies included very small number of samples. Ratio between variables and samples size was not considered in most papers and sufficient data size could not be achieved. Researchers also draw attention to the interdisciplinary nature of the field which constraints researchers' understanding of the experimental procedures as a result of being not familiar (Garcia et al., 2015: 177).

1.11 Literature Findings 2_Hybrid and Ensemble Classifiers

Guo et al. (2016) used ensemble learning approach based on classifiers including Decision Trees, Naïve Bayes and Support Vector Machines to construct credit scoring model based on social network data. Researchers indicated that unstructured social media could be applied to this type of classification model as input for credit scoring purposes.

Hsieh and Hung (2010) studied on ensemble classifiers as well. The proposed classifier was constructed based on Neural Networks, Support Vector Machines and Bayesian Networks. In order to enhance the ensemble classifier's performance class-wide classification approach was used before the process.

Dahiya et al. (2015) suggested an ensemble credit scoring model using 21 parameters for the model construction. Addo et al. (2018) constructed five models based on machine learning for predicting loan default, and comparing models' estimation performance based on AUC and RMSE measures. Compared models included Logistic Regression, Random Forests, Gradient Boosting Model and Deep Learning models. Performance of Random Forests and Gradient Boosting models outweighed the performance of other models.

Dahiya et al. (2015) worked on comparison of seven base classifiers and an ensemble model for credit scoring. CHAID, Neural Networks, Logistic Regression, CART, C5.1 algorithm, Support Vector Machines (SVM) and QUEST algorithm were considered for model construction. An ensemble model utilising these seven classifiers was also employed by incorporating classifiers according to the confidence-weighted voting approach. Logistic Regression model exhibited better performance than other base classifiers. However, ensemble model was superior to all other individual models. SVM performance was also close to performance of Logistic Regression model (Dahiya et al., 2015: 170).

Ala'Raj and Abbod (2016) suggested an ensemble model for credit scoring decision support system, which depends on group decision making approach. This approach was based on classifier consensus approach focusing on to combine output decisions of base classifiers. Neural Networks, Decision Trees, Support Vector Machines, Naïve Bayes and Random Forests were considered as base classifiers and their hybrid decision performance was compared with Logistics Regression and Multivariate Adaptive Regression Splines (MARS).

Cubiles-De-La-Vega et al. (2013: 6910) studied credit scoring within microfinance context and employed a set of classification algorithms for predicting default. In addition to examining base classifiers such as Decision Trees, Multilayer Perceptron, Support Vector Machines, Logistic Regression and Discriminant Analysis, Ensemble Models' performance was evaluated as well. Their findings proposed the utilisation of Multilayer Perceptron approach with revealing more accurate classification results.

One issue related with advanced classifiers is the organizational acceptance of advanced scoring methods. In some cases, regulatory issues and organizational acceptance may constitute barrier in front of the adoption of advanced scoring frameworks. However, the idea of dealing with advanced methods necessitate much more expertise in the field is not true. Full-automatic scoring approaches do not need human intervention in the case of risk assessment. Moreover, recent trend in the field of Big Data scoring and data-driven decision making may additionally increase the acceptability of advanced techniques (Lessmann et al., 2015)

1.12 Other Issues Regarding Credit Risk Models

1.12.1 Performance Evaluation Criteria of Credit Risk Models

Regarding the credit scoring era, models' performance measurement has been the topic of numerous studies as well. Predictive performance of credit scoring models have been evaluated by area under receiver operating characteristics (ROC Curves), average accuracy, Type I and Type II errors (Tounsi et al., 2017: 136). Depending on the fact that major goal of a credit scoring model is to distinguish good and bad loan applicants, performance of the model is measured by evaluating the accuracy of the classification performed by the model. Type I error occur when a good loan borrower is misclassified as bad loan borrower, while Type II error is observed when a bad loan borrower is misclassified as a good loan borrower (Cubiles-De-La-Vega et al., 2013: 6914). In addition to these metrics, more advanced techniques and performance evaluation criteria have been introduced for the credit scoring research area as well.

For instance, GINI and ROC curve were proposed as performance assessment metrics (H. A. Abdou and Pointon, 2011: 59). Yap et al. (2011: 13281) compared models that they built based on receiver operating characteristics (ROC) chart, Type I and Type II errors and validation misclassification rate. Blanco et al. (2013) compared the models' performance based on AUC and misclassification costs. ROC chart demonstrates percentage of loan defaults, which are estimated accurately as defaults, and percentage of non-defaults, which are categorized as defaults by mistake. In other words, ROC chart represents the proportion between true positives (sensitivity rate) and false negatives (specificity).The misclassification costs with regard to Type II error are much more than those related with Type I error (Yap et al., 2011: 13283).

Hand (2005: 1109) mentioned the Mean difference, Gini coefficient, The Kolmogorov Smirnov statistics and the Information value as the common important performance metrics in credit scoring and pointed out that at some cases these metrics can lead to misinterpretations and inappropriate conclusions. Hence, performance metrics are closely dependent on the construction methods of the credit scoring models and should be chosen accordingly.

Addo et al. (2018: 7) mentioned Area Under Curve (AUC), Akaike Information Criterion (AIC), Root Mean Square Error (RMSE) and Gini as metrics for performance comparison. GINI coefficient depends on Decision Trees approach and entropy metrics, while ROC approach deals with statistical calculation of the error. Blanco et al., 2013 (361) utilised AUC, Type I, Type II and misclassification cost measures to compare models' performance.

In order to compare performance of models, Ala’Raj and Abbod (2016: 96) stated that Average Accuracy (ACC), Type I and Type II Errors, AUC measure, Classification Error Rate and Brier Score have been utilised by the associated studies. ACC refers to percentage of accurately categorized good and bad credits with the aim of assessing model’s predicting or discriminating capability. AUC is the metrics utilised for classification of binary outcomes and no former information regarding the error costs is necessitated for performance evaluation. One limitation of AUC measure is that it employs different cost distribution between classifiers according to their existing score distribution. In contrast, H-measure does not employ different cost distribution without considering existing score distribution. Regarding the Brier Score, this measure evaluates at what extent the probability estimations are accurate. Brier Score is different from ACC metrics depending on the fact that it straightforwardly considers probabilities in contrast to ACC (Ala’Raj and Abbod, 2016: 96).

1.12.2 Feature Selection

Feature selection refers to a pre-processing method, which determines an alternative set of input variables by reducing features with low prediction performance. Feature selection has potential to enhance models’ accuracy and performance by producing a model with high variables that have high level of predictive information. There are numerous feature selection methods having differing search algorithms. Feature selection algorithm can either be in the form of embedded or filter. Wrapper is also another approach that is utilised to describe the link between the feature selection and the inducer. Some conventional machine learning techniques such as Neural Networks and Decision Trees are in embedded form (Mitchell, 1982, as cited in Dahiya et al., 2015: 167). Another feature selection technique is Chi-Square Statistics for choosing the most significant predictors. Features with the greatest Chi-Square values for a specific class demonstrate a good classification regarding the instances of that specific class. Hence, features demonstrating higher Chi-Square values are accepted for model construction (Dahiya et al., 2015: 167).

Design of Experiment (DOE) approach can be used for parameter selection process. Generally, performing grid search over the parameter set to explore the best combination of parameters is accepted as a simple and good method for parameter selection. However, this kind of research necessitates computational effort and takes time (Yu et al., 2011). Alternatively, DOE approach have capability of eliminating heavy computation burden when exploring the optimum model variables. Yu et al. (2011) also mentioned Genetic Algorithms and Direct Search as feature selection methods.

Heckman procedure was also proposed as an alternative to maximum likelihood approaches for defining the parameters of a model. Heckman procedure has two equations one of which is the selection equation and this is used for examining if a particular observation within the sample is creating non-random samples (He et al., 2016: 344).

CHAPTER 2: DATA SOURCES FOR CREDIT RISK MODELS

As the main goal in credit scoring decision support systems is to distinguish good and bad loans, classification is significantly important. However, this classification is dependent on a set of variables regarding the application. Anticipating factors correlated with outstanding debt and risky financial behaviours contribute to broaden our view of understanding about how to undertake the credit risk assessment issue in a more sophisticated manner. Predictor attributes are important as they define the selection of the classification algorithm and model construction approach.

Loan repayment is an outcome variable, which has two aspects including repayment capability and willingness to repay. A large number of factor affects repayment capacity. Willingness to repay is closely linked with strategic thinking of the borrower like cost benefit analysis of not repaying. Willingness to repay is also associated with honesty and the degree of undertaking of the borrower. As it is difficult to distinguish, whether the applicant do not have willingness to repay or is not capable of repaying it is instrumental to consider both factors and their correlates (Klinger et al., 2013: 58).

2.1 Factors Utilized For Estimation of Repayment and Default

Literature about creditworthiness and default prediction mainly concentrates on the decision making process of credit granting. These models usually depend on subjective selection of parameters, qualitative characteristics and deficient information (Gardner and Mills, 1989: 55). It is therefore, important to study parameters significantly correlated with probability of default. Some variables such as age, gender, and ethnicity are traditionally examined, or integrated into models for credit granting.

However, consumer debt is a growing phenomenon of today's modern age particularly in the context of developing countries. Traditional factors and models in consumer debt domain is not capable of explaining the factors behind repayment behaviour and serious debt of consumers, which results in delinquency. Consumer debt is a sophisticated problem that should be approached from a wide range of aspects. This multi-disciplinary view of aspect entails personality/psychology, behavioural and situational factors in addition to traditional factors such as payment history, demographical and socioeconomic factors.

Livingstone and Lunt (1992) claimed than the nature of the personal debt depends on a range of disciplines and should require an interdisciplinary view of aspect. Albeit much research has been conducted on the field of personal debt, debt repayment behaviour and factors differentiating debtors from non-debtors, recently no clear conceptual model that focus on evaluating psycho-behavioural profile of credit borrowers from a wide range of alternative data sources has been proposed. This psycho-behavioural profile by influencing individuals' financial decision making and credit behaviour put forth risks regarding the repayment behaviour of credit borrowers.

Economic psychology deals with daily matters in individuals lives likewise employment, actions, decisions associated with credit, debt, expenditure and investments. Recently, Economic Psychology and Behavioural Economics have led to the emergence of Behavioural Finance which has attracted considerable attention of academic surroundings (Ferreira, 2008, as cited in Rogers et al., 2015: 39). Behavioural Finance focuses on the behaviour in financial markets, and considers psychological perspectives when analysing changes and problems in financial markets. Therefore, economic psychologists have, therefore extensively examined credit or debt associated domains. This stream of research have tried to anticipate psychological profiles by including behavioural factors to give better conclusions regarding the individuals who are more likely to default, to have repayment problems or outstanding amount of debt (Rogers et al., 2015: 39).

Kamleitner, Hoelzl and Kirchler (2012) performed a systematic review on the credit use literature. Within classification framework of Kamleitner et al. (2012) research on credit use domain was classified based on the phenomenological aspects and afterwards a process view was implemented to further categorize the studies. Within the studies that considered the credit use as representation of the situation, the ones associated with credit use's prior stage, mostly mentioned demographical variables, life events, interest and credit opportunity. Situational aspect in the case of repayment stage focused on the repayment behaviour and its proposed determinants including financial variables, economic situation and spending behaviour. In the case of personal oriented perspective, a wide range of personality variables have been examined within the associated domain. In the case of repayment period, mental health, attitudes towards money and money management skills have been mentioned as the personal correlates of credit repayment (Kamleitner et al., 2012).

Researchers, who focused on the prior stages of credit usage from the cognitive view of aspect, have considered mental accounting and reasons for credit usage such as debt aversion. In the case of repayment stage, cognitive aspects oriented research have mentioned financial literacy, and thinking style of individuals as determinants of level of debt / problematic debt. Studies employing sociological perspective have underlined factors of social norms, parental norms, parental instructions and peer pressure. In the case of repayment period, social dynamics, consumption patterns, economic socialisation, others' attitudes towards debt have been pronounced within the sociological point of view (Kamleitner et al. 2012: 5).

This review represents an extensive list of factors that correlated with explanation of debt repayment behaviour and associated outcome domain. Research on credit utilisation and probability of default is highly extensive, thus parameters that extent research has explored to be significant indicators of default were considered within the scope of the model construction. These factors and their categorization under categories comprising; demographic, socioeconomic, behavioural, personality, situational and alternative provided an array of variables and their evolution over time. Prediction of probability of default is highly associated with the discipline of economic psychology, as a result of contemporary requirements and trends, this dissertation has concentrated on the factors discriminating individuals who repay their debts from the ones who do not pay and the factors affecting repayment of debt. Moreover, factors influencing people to go into debt that they cannot handle and to experience financial strain or delinquency.

Stone and Maury (2006: 547) stated that even the psychological variables were often statistically significant, they were not strong enough in predicting default or indebtedness when they were utilised individually. It was, therefore suggested that reliable models could be constructed by using these variables for complementary purposes.

2.1.1 Personality / Psychological Factors

According to Larsen and Buss (2008) personality comprises of a number of psychological properties that are arranged inside of an individual and this mechanism affects the way how he/she interacts with the environment. Personality traits are generally adjectives describing personal characteristics and these traits explain the difference between individuals at a wide extent. Previous literature has investigated a wide range of traits associated with human character by considering all probable facets. Personality traits have been the topic of research for the past several decades and has reached a consensus with Digman's (1990) Five Factor Model (FFM) comprising dimensions of; Extraversion, Agreeableness, Conscientiousness, Neuroticism and Openness to experience. McCrae and John (1992) emphasized the universal applicability of the model by arguing the emotional, personal, attitudinal and motivational differences that cause significant differences among individuals. For its representation of the structure of traits, FFM of personality has been implemented by many practitioners. Organization of personality traits and their representation by a particular taxonomy that can be quantified has been the topic of a remarkable number of research. Costa and McCrae's (1992) work which is called Big Five or FFM is a well-known taxonomy comprising five dimensions of personality. A significant amount of personality traits are organized around the dimensions of Conscientiousness, Neuroticism, Agreeableness, Extraversion and Openness to Experience (Ladas, 2016). Conventional banking approaches consider “character” seriously as a crucial aspect of creditworthiness. However, although many institutions suppose character, most of them do not make effort for measuring it in a quantitative manner (Caire, Andreeva and Johnson, n.d.).

Researchers also examined the impact of integrity on the probability of default as this trait involves lower willingness to back out. Big Five and Holland’s RIASEC vocational personality model have been among psychometric assessment tools that are used for numerous purposes. Five Factor or Big Five personality model comprising dimensions of Openness to Experience, Conscientiousness, Neuroticism/Emotional Stability, Extraversion and Agreeableness is accepted as the dominant model in the field of psychometric assessments (Klinger et al., 2013: 37). Employment selection, personality identification, intelligence and integrity tests are the most traditional implementations.

The utilization of virtual tests in psychometric evaluations instead of traditional Likert scales is less prone to “social desirability bias” which is defined as the error stemmed from the desire of establishing a good and acceptable personal image to others in order to abstain from potential embarrassment (Fisher, 1993). Regarding the credit risk assessment, the FFM has been used to dispose individuals based on their behavioural patterns in the case of credit utilization and repayment. One an example is VisualDNA's online image-based methodology for personality assessment. The virtual quiz of the VisualDNA which is based on a range of questions based on the FFM framework has been utilized in many commercial settings with the aim of assessing probability of default risk of credit borrowers and their behaviour against credit repayment (VisualDNA, 2014).

Caire et al. (n.d.) stated that willingness to repay could be predicted with personality factors in the case of limited information regarding the applicants. Conscientiousness, agreeableness, integrity, locus of control, risk taking and cognitive ability are among some personality correlates of probability of default that was explored (Caire et al., n.d.).

Correlates of probability of default might not have the equivalent meaning across different cultures. Klinger et al. (2013: 85) indicated that psychometric tools such as Big Five personality assessment revealed mixed findings across cultures. Consequently, it is challenging to examine at what extent personality indicators vary across cultures. Klinger et al. (2013: 69) conducted a cross-cultural study to assess psychometric traits' relationship with default across Africa and Latin America. Findings disclosed that neuroticism was significantly related with default, while extraversion and conscientiousness did not demonstrate a strong association in different cultural contexts. However, in most cases conscientiousness was negatively linked with default risk.

2.1.1.1 Conscientiousness

Davey and George (2011) investigated the influence of conscientiousness on financial behaviour and discovered a strong correlation. Routh and Burgoyne (1991) presented the results of their study, which revealed that less conscientious individuals were inattentive about their financials. Brown and Taylor (2014) found out that conscientiousness was negatively linked with the levels of debt. Gagarina and Shantseva (2017) revealed the similar results demonstrating that debtors had lower levels of conscientiousness.

2.1.1.2 Neuroticism

Neuroticism is an expression utilised to depict individuals who are inclined to experience depression, mood changes and anxiety (Harrison and Chudry, 2011). Emotional instability (neuroticism) is defined as the inclination of feeling a set of negative emotions such as anxiety, envy, anger and depression (Costa and McCrae, 1992). Harrison and Chudry (2011) indicated that for individuals having high scores on neuroticism, money seems to be an influencer of anxiety. Thus, their decision making in financial issues is affected. However, they found out that no significant relationship existed between neuroticism and indebtedness. In addition, Rushton and Chrisjohn (1981) did not find a meaningful relationship between delinquency and neuroticism. On the contrary, Addad and Leslau (1990) discovered a relation between neuroticism and delinquent behaviour. Duijsens and Diekstra (1996) found a positive correlation with impulsiveness and neuroticism in addition to a set of psychological disorders. Bivens, Gore and Claycomb (2013) investigated the correlation of compulsive buying and Big Five personality traits and discovered a strong positive correlation between neuroticism, and impulsiveness and compulsiveness. Nyhus and Webley (2001) discovered that emotional instability was correlated with debt. Davey and George (2011) also discovered a significant link between organized financial behaviour and low scores on neuroticism.

2.1.1.3 Extraversion

Extraversion is generally associated with outgoing, sociable, talkative, assertive, passionate, energetic and enthusiastic individuals (Zainol et al., 2016). Research correlating extraversion with problematic debt depends on the fact that extraverts are inclined to have high expenditures, as a result of their social life and outgoing character. Nyhus and Webley (2001) discovered extraversion to be a significant indicator of economic behaviour. Davey and George, (2011) discovered a strong relationship between extraversion and financial behaviour in terms of debt level. Rushton and Chrisjohn (1981) tested the Eysenck's theory associated with the link between delinquency and, extraversion and neuroticism. "According to this theory, extravert subjects condition less well than introverts and thus fail to develop social responses which will serve to contain the universally present propensity to crime" (Addad and Leslau, 1990: 3). Some results demonstrated that delinquency was positively correlated with extraversion. Harrison and Chudry (2011) discovered a significant link between debt behaviour (history of overdraft debt) and extraversion. Zainol et al. (2016) also discovered that extraversion was correlated with individual indebtedness. Brown and Taylor (2014) discovered a significant relationship between extraversion and levels of debt. On contrary, Addad and Leslau (1990) did not find a significant relation between extraversion and delinquent behaviour.

2.1.1.4 Agreeableness

Agreeableness is an expression characterizing cooperative, helpful and compatible people who are easy-going. People who are not agreeable are prone to be unfriendly, distrustful and noncompliant (Office of the Director of National Intelligence, 2011). Yang and Lester (2014) discovered that lower scores on agreeableness is associated with high amount of credit card debt. Nyhus and Webley (2001) investigated financial behaviour and its relationship with agreeableness and they discovered that high scores on agreeableness is linked with borrowing behaviour. Davey and George (2011) discovered a strong relationship between agreeableness and financial behaviour.

2.1.1.5 Openness to Experience

Open-minded individuals and people having a tendency of exploring new ideas and things is characterised by openness. Less openness indicates the tendency of preserving the existing situation without being interested in innovative things and ideas. Yang and Lester (2014) discovered that high scores on openness is associated with high amount of credit card debt and foreclosure. Zainol et al., (2016) also discovered that openness is correlated with individual indebtedness.

2.1.1.6 Self-Control

Baumeister, Bratslavsky, Muraven and Tice (1998) pointed out that self-control is the ability of dealing with temptations and keeping up self-discipline. Individuals possess high levels of self-control are found to cope better with consumption impulses. Self-control refers to the capability of leaving bad habits, withstanding temptations and coping with impulses (Baumeister, 2002, as cited in Strömbäck et al., 2017: 30). The behavioural life cycle (BLC) hypothesis claims that capability of controlling impulses is the major element of financial behaviour throughout life (Strömbäck et al., 2017: 31).

Hence, studies investigating problematic debt levels and its reasons also concentrated on self-control problems and compulsive buying. Impulsive buying refers to a self-control instrument which reflects imprudent, purposeless and tempting decision making (Limerick and Peltier, 2014). Thus, compulsive buying is associated with problems in controlling impulses and impulsivity. According to Kamleitner et al. (2012) self-control dominates compulsive buying and going into debt.

Limerick and Peltier (2014) handled the measurement of self-control in an untraditional way by comprising the variables of external locus of control, impulsivity, social status and poor debt management. They discovered that these variables jointly influence the amount of debt. Lack of self-control is explored to be an indicator of tendency to have extensive debt levels (Livingstone and Lunt, 1992; Wang et al., 2011; Rogers et al., 2015; Nyhus and Webley, 2001; Limerick and Peltier, 2014). Meier and Sprenger (2010) discovered a link between impatience and credit card misuse. Claes et al. (2010), Romal and Kaplan (1995) and Achtziger, Hubert, Kenning, Raab and Reisch (2015) explored significant influence for self-control as well.

Ridder et al. (2012) correlated low levels of self-control with bad decision making about purchases. Mansfield, Pinto and Parente (2003) indicated that risk taking behaviour, which is a facet of self-control is significantly correlated with credit debt levels. Ameriks, Caplin, Leahy and Tyler (2004) reported that personal differences in terms of self-control are associated with personality. Among the personality factors of “Big Five”, conscientiousness is strongly correlated with self-control.

2.1.1.7 Impulsiveness

Impulsivity is associated with making instantaneous decisions without thinking its consequences. Premeditation, urgency, sensation-seeking and lack of perseverance are among the facets of impulsivity (Office of the Director of National Intelligence, 2011). Previous literature attracted attention to the complexity of this personality trait by revealing its relationship with different facets of conscientiousness, neuroticism and extraversion. Thus, these traits’ meanings overlap with the impulsivity to a particular extent (Office of the Director of National Intelligence, 2011).

Sensation seeking is one of the personality factors that is correlated with consumer debt in the literature. This trait is associated with individuals who have great tendency of taking financial and social risks so as to experience some complex and intense feelings.

“Sensation-seeking is a class of psychological traits that reflect characteristics of extroversion and impulsivity in an individual's behaviour (i.e., thrill and adventure-seeking, experience-seeking, disinhibition and boredom-susceptibility)” (Harlow and Brown, 1990). Kamleitner et al. (2012) discovered that sensation-seekers differed significantly than low sensation seekers in terms of problematic financial behaviours as a result of taking more risks. However, Wang et al. (2011) found controversial results. Tokunaga (1993) investigated the factors differentiating people who are and are not capable of using credit effectively. He discovered that unsuccessful credit users had lower risk taking and sensation-seeking inclinations.

2.1.1.8 Locus of Control (LOC)

In searching for variables associated with problematic debt, it was discovered that the psychological variable “locus of control” had been found to predict individuals with high levels of debt and bad repayment behaviour. If the source of an event’s occurrence is believed to be luck, chance, fate or any other surrounding forces except from one’s own by an individual, this belief is called external control. In contrast, if a person accepts himself/herself’ and his/her behaviours as the origin of events the term internal control is utilized so as to define his/her belief. It defines at what extent people believe that they have control over their life (Rotter, 1966). LOC is regarded as a major personality variable depending on the fact that it is closely associated with performance and motivation (Perry, 2008).

A group of research examined the correlation of Perceived Behavioural Control (PBC) and debt repayment behaviour. According to Ajzen (1991), Perceived Behavioural Control (PBC) differs from LOC in terms of its consideration of a more particular situation and perception of regarding its control. On the other hand, LOC is more about general view of an individual about the source of events happening and anticipation of its control (Kennedy, 2013). External locus of control was found to be an indicator of signifying debtors from non-debtors (Ding, Chang and Liu, 2009; Dessart and Kuylen, 1986; Livingstone and Lunt, 1992; Tokunaga, 1993; Wang, Lu and Malhotra, 2011; Mewse, Lea and Wrapson, 2010; Kennedy, 2013; Limerick and Peltier, 2014).

Moreover, Perry (2008) indicated that individuals with higher credit scores had internal locus of control and external locus of control was negatively correlated with planning, budgeting and saving skills. Davey and George (2011) also found out a strong relation between LOC and financial behaviour. Moreover, Ding et al. (2009) discovered a direct link between external LOC and intention not to repay. However, some researchers found that there is no significant link between LOC and levels of debt (Lea, et al., 1995; Davies and Lea, 1995).

2.1.1.9 Self-Esteem

Self-esteem refers to one's beliefs and perceptions regarding his / her own value or worth and reflects his / her anticipations about how others see him / her (Omar et al., 2014: 55). Materialism refers to commitment to material ambitions and having desire of possessing material things. Materialists often see possessions as symbols of success and possession is an instrument for life satisfaction. Credit is a tool for achieving those goals, however it is temporary and does not depend on actual resources. It is therefore, suggested that this kind of desire can easily provoke temptation, high level of spending and credit misuse (Omar et al., 2014: 56).

2.1.2 Situational Factors

Social scientists that concentrate on psychological well-being, discovered social patterns and social factors that influence people's psychological state in addition to personality factors (Drentea, 2000). Agnew (2001) who is the constructer of the General Strain Theory (GST) indicated that confronting strains or stressors influence individuals' well-being in a negative way and might cause criminal behaviours. Foundation of the theory comprises the definition of strain types, link between stressors and criminal behaviours and the reasons behind reacting strains with crime. Disliked events and conditions (strains) defined by the theory are considered as some remarkable direct and indirect causes of crime. These influences lead to different types of delinquency by means of triggering anger and depression. Moon et al. (2009) concentrated on the GST as well and investigated the correlation between delinquency, and situational and trait-based negative emotions. This research stream encapsulated various sources of strain such as difficulties with other people, property victimization, physical and emotional abuse, and negative life events (e.g., divorce, criminal victimization) and their influence on delinquent behaviour (Moon et al., 2009). Trait-based negative emotions including anger, anxiety and depression, and their link with delinquency have been proposed by many researchers

(Aseltine, Gore and Gordon, 2000; Baron, 2004; Mazerolle, 1998; Mazerolle and Maahs, 2000; Mazerolle and Piquero, 1997; Moon and Morash, 2017). Piquero and Sealock (2000) discovered significant influence as well.

Specifically, Drentea (2000) investigated the link between anxiety and debt. Simmons (2013) conducted a research on the relationship of mental health and consumer debt. Nelson et al. (2008) investigated the link between stress and debt. On the other hand, some research on GST focused on the situation-based negative emotions and their relationship with delinquency. These conditioning factors were considered “emotional states”, which were switched as a result of exposure to strains whereas trait-based negative emotions were regarded as general tendency to undergo particular emotions (Agnew, 2006). A wide range of researchers have tested GST theory in order to evaluate which types of strains resulted in delinquency and as a result, negative life events and life troubles were highly correlated with delinquency (Agnew, 2001). Hereby, the theory (GST) is logically related to the research stream, which investigated the situation-based negative emotions and specifically their link with delinquency in a financial sense. It was indicated that financial losses are highly correlated with stress and debtors tended to have more stress, anxiety and psychological agony (S. Lea, n.d.). Thus, a broad range of articles (Conger and Conger, 2002; Drentea, 2000; Santiago, Wadsworth and Stump, 2011; Nelson et al., 2008; Ridgway, Kukar-Kinney and Monroe, 2008; Simmons, 2013) discussed the link between stress, emotional distress and financial issues. J. Kim, Garman and Sorhaindo, (2003) discovered link between stressful events and financial behaviour.

One route into debt that has been studied is the correlation of debt with situational factors. Situational factors have also been considered as components of a multi-disciplinary behavioural model of creditworthiness and have been specified including unexpected situations that resulted in financial constraints in individuals’ life. Situational Factors are life altering events comprising death of a spouse, divorce, marital separation, jail term, death of a close family member, personal injury or illness, marriage, retirement, change in health of family member and pregnancy, etc. according to Holmes and Rahe's (1967) Social Readjustment Rating Scale. This scale was constructed based on possible stressful events that one may encounter and most research associated occurrence of these events more than once within the last 12 months with problematic debt. Thus, these factors were associated with the situational occurrences and adverse events in peoples' life. Several studies mentioned situational factors in the context of explaining the outcome domain associated with debt and repayment behaviour (J. P. Hoffmann and Miller, 1998; Stone and Maury, 2006; Tokunaga, 1993; Rogers et al., 2015). J. P. Hoffmann and Cerbone (1999), J. Hoffmann and Su (1997) and Mirowsky and Ross, (1999) investigated the influence of situational factors as well.

Consideration of adverse life events is important to explore particular reasons behind bankruptcy and default situations (Chakravarty and Rhee, 1999: 10; Costa, 2012). With regard to situational variables, Gardner and Mills (1989) discovered that job loss, health problems, financial & legal matters are among reasons for delinquent behaviour. Avery, Calem and Canner (2004) conducted research on how situational circumstances affect the capability of credit scoring models. Specifically, certain types of situational data such as local economic conditions and individual trigger events were considered in the study. They mentioned the practical difficulties in integrating situational data into credit scoring processes.

2.1.3 Values, Attitudes and Behavioural Factors

Theory of Planned Behaviour (TPB) has been widely used as a framework for anticipating financial behaviour such as borrowing attitudes and the level of debt (Kennedy, 2013: 2). Near the earliest predictors of the theory, Ajzen (2008) indicated that additional parameters could be added to the theory as far as they are behaviour-centric and independent from theory's original parameters (as cited in Kennedy, 2013: 6). Financial behaviour research widely adopted TPB which concentrates on anticipating human behaviour (Ajzen, 1991, as cited in Xiao, 2008: 69). This theory is the expanded version of the Theory of Reasoned Behaviour, which was proposed by Fishbein in 1967. Theory of Reasoned Behaviour claims that intention is the main driver of a particular behaviour. Intention has three major components: attitudes towards behaviour, subjective norms and the attention put on the attitude and subjective norms (Ajzen and Fishbein, 1980, as cited in Xiao, 2008: 73). Afterwards, when the dimension of perceived control was added, TPB emerged as depicted in Figure 2.

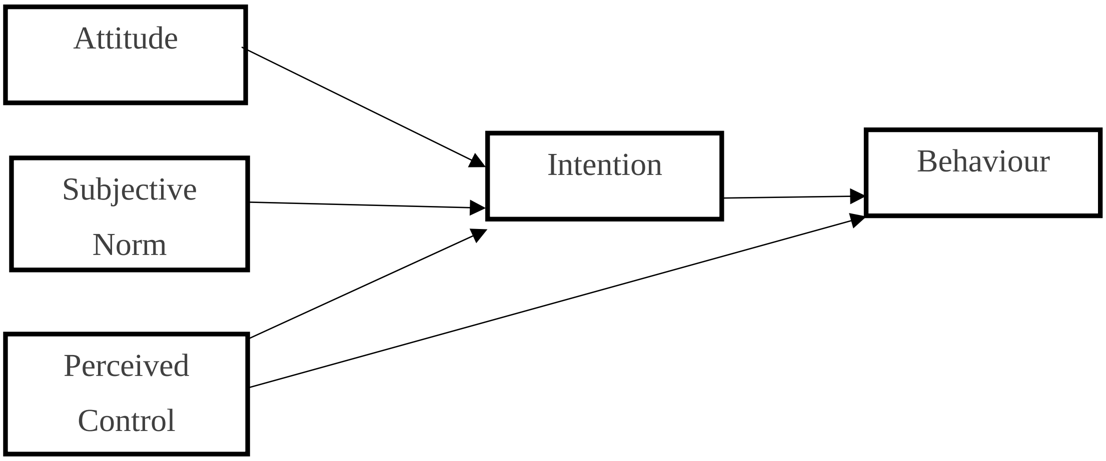

Figure 2: Theory of Planned Behaviour

Source: Ajzen (1991)

Attitude explains at what extent an individual holds a favourable or unfavourable position with regard to support of the behaviour questioned (Kennedy, 2013: 7). Attitudes towards debt may be affected by attitudes towards money, tolerance to debt, financial literacy, locus of control and unrealistic optimism with regard to future finance (Kennedy, 2013: 7). Attitude has three aspects including affective, behaviour and cognitive. For instance, regarding the behaviour of credit card utilisation, greater scores on the affective dimension indicates willingness to use credit cards. Cognitive dimension is associated with knowledge about credit cards, whereas behaviour dimension involves willingness to possess more credit cards (L. Wang, Lv, et al., 2011: 125).

Principally, attitudes are described as people’s sensations, assumptions and common approach towards a particular phenomenon (Funder, 2001, as cited in von Stumm et al., 2013: 344). Opposed to personality they are more changeable as a result of being influenced by situational factors. Differences among people in terms of approaches to money matters, attitudes towards money have been conceptualised by the previous literature by identifying different money attitudes (von Stumm et al., 2013: 344).

Subjective norms are described as the perceived social pressure over individuals with regard to involving in a particular behaviour (Ajzen, 2008, as cited in Kennedy, 2013: 14). Based on the social comparison theory, individuals that are prone to influence of subjective norms are widely described as ones who are putting effort to “keep up with the Joneses”. It is, therefore proposed that subjective norms might have impact on the financial behaviour of people and accumulation of debt, especially when individuals compare themselves with the others based on possession of money and objects (Lea et al., 1995, as cited in Kennedy, 2013: 14).

Perceived control is associated with perceived level of effort for carrying out that behaviour and subjective norm identifies ones perceptions whether or not others approve or disapprove a particular behaviour (Xiao, 2008: 73). Theory of Planned Behaviour have been applied to many different settings such as consumer behaviour in financial services, debt management and e-commerce (Xiao, 2008: 75). Even though only a few studies have investigated the act of perceived behavioural control in debt behaviour, they demonstrated valuable findings. For instance, perceived behavioural control is discovered to be a negative antecedent of level of debt. In similar studies, even if the two constructs are different, locus of control or self-efficacy have often been treated as perceived behavioural control (Kennedy, 2013: 19). Hence, vast amount of studies investigated the effect of locus of control and self-efficacy on the financial behaviour and level of debt.

Family resource management theory and Bandura's social learning theory could be used to anticipate influencers of credit behaviour (Deacon and Firebaugh, 1981; Bandura, 1977, as cited in Hancock et al., 2013: 370). Family resource management theory indicates that behaviours are consequences of demands and goals for the utilisation of resources. Input elements of the theory are often personal characteristics and environmental influencers and throughputs are financial attitudes and knowledge. Level of debt can be considered as the output of the conceptual model. Bandura's social learning theory suggests interactions at a particular environment shape individuals' financial attitudes and knowledge. It is, therefore proposed that parental socialisation is important and together with other environmental influencers they affect financial attitudes. Financial attitudes have a mediating effect on the relationship of environmental influencers and the outcome variable, which is the credit card debt in this case (Hancock et al., 2013).

Kennedy (2013) also utilised Ajzen's (1991) theory in order to estimate level of debt of college students. The theory is expanded so as to include financial literacy of students to test this variable's predictive capability. Among variables of perceived behavioural control, attitudes towards credit, financial literacy and subjective norms, all of the variables except from financial literacy significantly predicted the outcome variable.

2.1.3.1 Compulsive Buying

Compulsive buying has been topic of consumer research literature for the past three decades since it was first introduced (Faber, O'Quinn and Krych, 1987, as cited in Ridgway, Kukar-Kinney and Monroe, 2008). Compulsive buying having theoretical foundations in obsessive-compulsive spectrum disorder is defined as the individuals' inclination of being mentally caught up in buying which results in buying in a repetitious manner and impulsively. According to study of Ridgway et al. (2008) compulsive buying concept has two main dimensions comprising obsessive-compulsiveness and impulsiveness. Compulsive buying was first defined as a disorder which is associated with "chronic, repetitive purchasing that becomes a primary response to negative events or feelings" (O'Guinn and Faber, 1989: 155). Goldsmith and McElroy (2000) indicated that compulsive buying often causes financial problems comprising indebtedness and bankruptcy. Similarly, some researchers indicated that credit card misuse is correlated with compulsive buying (Palan, Morrow, Trapp and Blackburn, 2011; Pirog and Roberts, 2007). Phau and Woo (2008) discovered significant link as well.

Impulse buying happens when a consumer suddenly feels strong desire and impulse towards purchasing something instantly. An immediate urge fosters an individual to perform a particular behaviour like purchasing an object immediately without considering its consequences and without postponing. Impulse buying might stem from instant self-control failure and might result in negative outcomes (J. Wang and Xiao, 2009: 3). Pirog and Roberts (2007) indicated that misuse of credit could be explained by impulse buying. Delay of gratification refers to deferring of gratification in purchasing behaviour or in other situations (Norvilitis, 2014: 639).

Decision making is closely related with personality traits and it influences shopping motivations. Thus a significant number of research investigated the relationship between "Big Five" personality traits and consumer behaviour (Gohary and Hanzaee, 2014). A number of research has been devoted to investigate personality traits and compulsive buying. Conscientiousness is a dimension of Big Five which defines planned, well-organized, self-disciplined, dutiful individuals that mostly demonstrate perfectionists' attitudes (Zurawicki, 2010, as cited in Gohary and Hanzaee, 2014). A number of research have discovered a negative relationship between compulsive buying and conscientiousness (Mowen and Spears, 1999; Gohary and Hanzaee, 2014). Neuroticism, which is another Big Five trait is also found to be correlated with compulsive buying (Johnson and Attmann, 2009). Pirog and Roberts (2007) pointed out that introversion is positively related with compulsive buying. On the contrary, Balabanis (2002) discovered a positive relationship between extraversion and compulsive buying whereas agreeableness and openness to experience are found to be negatively correlated.

2.1.3.2 Social Comparison

According to Festinger (1954) Social Comparison Theory people have the tendency of evaluating themselves compared to others. It is a strong psychological drive that directs people's behaviour and decisions. When people want to find out about themselves, their achievements and weaknesses, they have a powerful motive to compare themselves with the others. Corcoran, Crusius and Mussweiler (2011) stated that social comparison is described as the requirement of revealing one's identity by means of consumption and social status. Thus, literature related the social comparison with amount of debt (S. E. G. Lea et al., 1995). Rogers et al. (2015) also considered the social comparisons as an influencing factor behind problematic debt situations and investigated its effect of differentiating the individuals who have or do not have problems with debt even if their economic situation is similar.

2.1.3.3 Attitudes Towards Money

Previous studies investigating the link between money and behaviour revealed numerous relationship. The study of Yamauchi and Templer (1982) is the first attempt for development of a scale for measuring attitudes towards money (as cited in Hayes, 2006). Final version of the scale is known as the money attitude scale (MAS) with four dimensions comprising power & prestige, distrust, anxiety and retention & time. Furnham (1984) put on the other attempt with the aim of assessing money beliefs and behaviours and explored dimensions of obsession, security / conservative, power / spending, inadequate, retention and effort / ability (as cited in Hayes, 2006). Previous researchers found particular attitudes towards money might affect the financial behaviour. Obsession explains at what extent the individual considers different elements of money and power /

spending indicates that the individual feel strong as far as he / she spends money. Retention refers to keeping away from spending money. Security explains the behaviour of thinking deeply about consequences and risks of financial behaviour. Inadequacy means spending behaviour to cope with feeling awkward and effort / inability explains at what extent the individuals believe that they deserve their income (Kennedy, 2013: 10-11).

Attitudes towards money is an important factor as correlate of debt and financial behaviour and previous research indicated that power & prestige dimension of money attitude is significantly linked with compulsive buying which may result in accumulating high levels of debt. Retention is the dimension of attitudes toward money, which is associated with being cautious in spending money, planning budget and saving (Harper, 2015).

Harper (2015) investigated the relationship between credit card utilisation and compulsive buying. The influence of attitudes towards money is also considered. It is discovered that those who see money as a power & prestige symbol are more likely to accumulate more credit card debt and to be a compulsive spender. Although the study also considered the retention dimension of money attitudes, no significant relationship is observed with the level of debt. Nepomuceno and Laroche (2015) specifically examined consumption related with life style and materialism on level of debt. Three dimensions associated with materialism (happiness, success, centrality) and anti–consumption lifestyle (frugality, tightwadism, voluntary simplicity) are considered. Happiness, success dimensions of materialism and voluntary simplicity dimension of anti-consumption life style were significant determinants of level of debt. L. Wang, Lv and Jiang (2011) specifically focused on a behavioural model for predicting debt repayment behaviour. Attitudes towards money, credit, debt and risk are investigated among a Chinese sample. It is discovered that positive attitudes towards debt, viewing money as power & prestige symbol had significant contribution on negative repayment behaviour. Also, participants with higher scores on affective and behaviour dimensions of credit attitudes are more likely to exhibit bad repayment behaviour.

2.1.3.4 Financial Well-Being

The degree of individuals' financial health is often conceptualised by the term financial wellness. Financial wellness concept has more than one aspect associated with financial satisfaction, objective financial conditions, attitudes and behaviours. Other concepts relating to financial wellness are economic well-being, financial well-being and well-being (Xiao, 2008: 22). Some proxies are utilised to measure financial wellness comprising income, financial behaviour, satisfaction and wealth. Wealth is generally utilised with alternative wellness measures likewise income (Xiao, 2008: 24).

Financial well-being can be assessed through personal financial management. Hence, behavioural aspects of financial management have been utilised for quantifying financial well-being. Financial management comprises financial planning, financial practices such as purchasing and banking, management of income, utilisation of credit and savings & investing for the future (Garman and Forgue, 2006; Mathus, 1989, as cited in Xiao, 2008: 25). Another behaviour revealing financial well-being is financial adjustment like other sources of debt or investigations for borrowing. Financial knowledge, debt and credit management, savings and assets are also associated with the financial behaviour. Subjective perception component of well-being can be measured through financial attitudes and financial knowledge (Xiao, 2008: 30). Financial ratios are also utilised for assessing individuals' financial well-being. Past financial ratios such as debt-to-income ratio and living expense-to-income ratio can be used for evaluating more recent and objective financial status as it is accepted that subjective perception is a leading force for wise financial behaviour (Xiao, 2008: 26).

2.1.3.5 Financial Literacy

Financial decisions of individuals are important in evaluating correlates of default risk and the relevant literature has investigated the effect of financial decisions from different perspectives. Low levels of cognitive capacity may affect the individuals' contract preferences and may prevent anticipating future consequences. Contrarily, higher levels of financial literacy means better understanding over terms and conditions and choosing profitable credit options with better repayment terms. Low level of cognitive and numerical ability is also closely associated with poor saving and budgeting behaviour, inadequate financial planning, and decisions, and credit card misuse. Hence, individuals having limited financial literacy are more vulnerable to default (Gerardi, Goette and Meier, 2013). Financial literacy as a reflection of poor decision making in financial issues have been investigated with regard to its correlation with default status or high levels of debt. A considerable number of research discovered a positive association between financial literacy and behaviour. For instance, Gerardi, Goette and Meier (2013) investigated the influence of financial literacy and capability of performing basic numerical calculations on probability of mortgage default. Results remarked the strong negative association between default tendency and financial literacy.

2.1.3.6 Economic Socialisation

Economic socialisation is described as the process which financial behaviour of individuals are shaped by their family. It is proposed that people' more inclination to debt might be a consequence of economic socialisation (Lea et al., 1995, as cited in Kennedy, 2013: 16). Tokunaga (1993) emphasized the influence of parents on credit utilisation of participants as well and indicated that responsible behaviour in credit utilisation could be explained by the parents' responsible and proper behaviour in financial management.

Some research focused on the economic socialisation of individuals, which deals with progressional competencies in anticipating and involving in economic processes. Some particular agents of economic socialisation such as parents, culture, peers and media, and their impact on individuals are examined. A considerable amount of research have investigated the act of parents in economic socialisation. It is therefore claimed that parents have impact on passing attitudes, skills and behaviours such as delaying gratification, attitudes towards money and prudence (Xiao, 2008: 95). Hence, impact of parental guidance and parental instructions have been examined as correlates of credit misuse or debt management literature. Parental influence is accepted as the most important socialization agent and its consequences are long-term (Moore et al., 2002, as cited in Xiao et al., 2011: 240). Social motivation is described as an individual's beliefs and perceptions with regard to other important people's approval for a particular behaviour. In other words, social motivation refers to the one's degree of getting other people's assistance and advice for performing a certain behaviour and his/her inclination to pay attention to that behaviour (Limbu, 2017: 845-846).

2.1.3.7 Risk Aversion

Risk taking propensity is strongly believed to be related with ethical decision making. Risk taking is associated with the extent to which an individual looks for to be subjected to uncertainty, particularly with regard to financial benefits or losses. Thus, this personality trait is associated with the tendency of an individual to either look for or avoid risk (Kowert and Hermann, 1997, as cited in Ding et al., 2009: 817). Previous studies have shown that risk taking propensity is associated with unethical behaviour (Ding et al., 2009: 817). L. Wang, Lv, et al. (2011) explored that attitudes towards risk significantly predicted credit misuse.

2.1.3.8 Consideration of Future Consequences

Joireman, Kees and Sprott (2010) claimed that consideration of future consequences had presented significant link with financial decision making. Consideration of future consequences (CFC) refers to the level of consideration of probable results of current actions and behaviour, and individuals with a high level of CFC put greater attention on future outcomes of their behaviours. Joireman et al. (2010) examined the effects of consideration of future consequences and compulsive buying on level of debt of college students in U.S. Consideration of future consequences is negatively linked with the level of debt while compulsive buying showed positive association.

2.1.3.9 Time Preferences

Based on life cycle hypothesis Ando and Modigliani (1963) indicated that individuals savings and consumption patterns are associated with life cycle stage of individuals, age and life cycle stage are important influencers of savings and consumption which is expected to influence the level of debt a household has (Yilmazer and DeVaney, 2005: 287). Kim and DeVaney (2001: 67-68) based on life cycle model for explanation of household consumption, proposed that repayment behaviour and outstanding credit card debt are influenced by consumers' requirements, available resources, interest rate and consumers' choices. Time preference described as the consumer's willingness to adjust consumption over life. Borrowing is a result of desire for enhancing existing consumption by moving future resources to the present. When resources of today are not adequate, consumers decide to borrow for utility maximization. Hence, time preference is closely associated with willingness to borrow. Time horizon, which is associated with time preferences suggests that individuals that mostly appreciate present rather than the future have more tendency to borrow money (as cited in Kim and DeVaney, 2001: 68). Thus, people with shorter planning horizon are believed to be more prone to outstanding debt accumulation (Kim and DeVaney, 2001: 70).

2.1.3.10 Financial Management

Fitzsimmons, Hira, Bauer and Hafstrom (1993) reviewed financial behaviour research by specifically focusing on variables of financial management. Financial behaviour refers to any kind of behaviour associated with money management and some prevalent financial behaviours comprise debt, credit, spending and saving behaviour (Xiao, 2008: 70). Credit card misuse is described as behaving irresponsibly and performing high level of spending when using credit cards that results in outstanding debt (Limbu, 2017: 843). Money management skills comprising budgeting, investment, credit utilisation, debt accumulation and savings have been investigated with regard to their impact on financial behaviour problems.

Savings and borrowing attitudes are related with consumption styles in the course of time and future beliefs. Conventional aspects of economists to the phenomenon anticipates debt or saving as an instrument of adjusting consumption based on foreseen future income. Relevant theories depend on the rationale of realistic individuals having balanced clear-cut preferences are inclined to borrow based on future income. Noteworthy number of evidence, people without capability of amend over time principally do not have enough self-control to maintain their plan (Anderson and Nevitte, 2006: 248). Hence, Anderson and Nevitte (2006) examined the impact of thrift and saving behaviour on the level of debt.

Credit cards and their use is another aspect of credit behaviour as it reflects at what extent a borrower uses credit responsibly. Risky credit card behaviour emphasizes behaviour associated with financial behaviour and is associated with future financial problems (Robb, 2011: 693). Credit card debt is accepted as one of the most ambiguous type of consumer debt, and it was therefore claimed that it might be a more accurate measure of financial well-being compared to income. One reason behind this matter is the accumulation of the credit card debt over time, which reflects long run financial problems (Kennedy, 2013: 3).

Level of debt is an outcome of negative financial behaviour, whereas savings and decreased debt are among outcomes of positive financial behaviour. Behaviours partially cause those outcomes (Ajzen and Fishbein, 1980, as cited in Xiao, 2008: 70). A single act is a particular behaviour of an individual for instance utilisation of credit card for outfit purchases and a number of single acts serve to define a financial behaviour. Most financial behaviours are defined through a number of single acts (Xiao, 2008: 71). Most research use perceived behaviour and self-efficacy interchangeably although they are different concepts. Xiao (2008: 74) reported that self-efficacy is more capable of predicting behaviour.

Most research within the creditworthiness assessment or default estimation mostly considered responsible / irresponsible financial behaviour including credit or credit card misuse and the level of debt as a result of financial behaviour. These variables mostly comprise the domain for the outcome variables or independent variables utilised in the studies.

2.1.4 Demographic Factors

A number of theories try to explain changes in peoples' lives, as they get older. For instance income, consumption and expenditure of people change over the life cycle. The life cycle hypothesis of savings proposes that individuals preserve a certain level of consumption throughout their life-time. Young individuals, therefore try to borrow more in order to consume compared to middle aged, who are able to save some amount of their earnings (Xiao, 2008: 220). The permanent income hypothesis claims that people adopt their consuming and expenditure according to their beliefs with regard to their future income and precautionary savings model suggests that old people are more attentive in consuming their assets (Xiao, 2008: 211).

Thus, a significant amount of research focusing on creditworthiness integrated the parameter of family life cycle stage for the assessment. Effect of marriage of financial behaviour can be considered within this domain due to family consumption and expenditure differences. Xiao (2008: 339) indicated that marriage alters peoples' connection with money. Income and wealth status of married individuals are different which necessitates special attention for marital status in assessing creditworthiness. Behaviour of men and women are not the same. Broad scope longitudinal samples demonstrated that accumulation of debt, savings and expenditure differed significantly among genders (Zagorsky, 2003, as cited in Xiao, 2008: 342).

Accordingly, demographic factors including age, gender, marital status, ethnicity and family life cycle stage have been widely integrated into credit risk models for predicting default, repayment behaviour or level of debt (Gray, 1985; Wilms et al., 1987; Tokunaga, 1993; S. E. G. Lea, Webley and Levine, 1993; Y. I. W. Chien and Devaney, 2001; Drentea, 2000; L. Wang et al., 2011; Baek and Hong, 2004; H. Abdou et al., 2008; Mewse, Lea, and Wrapson, 2010; S. Costa, 2012; Y. Wang et al., 2013; Bryan et al., 2010). Kočenda and Vojtek (2011) and Ge, Feng, Gu and Zhang (2017) incorporated demographic factors in risk models as well.

2.1.5 Socioeconomic Factors

In order to anticipate risk factors causing adverse financial outcomes such as default, bankruptcy, missing payments or becoming in arrears, socioeconomic conditions such as income level, occupation and education should be considered. Part of the society with low-income are often very sensitive to economic fluctuations, as a result of possessing less financial safeguards (von Stumm et al., 2013: 345).

A wide range of indicators are utilised to anticipate economic status of individuals. These are income, poverty related indicators, net worth of total assets, liquid assets, non-financial assets, consumption and expenditure patterns, debt, employment status and home ownership status (Xiao, 2008: 211-216). Savings and amount of assets are associated with wealth. Thus, a number of wealth indicators such as home ownership and vehicle ownership have been used in decision making systems for credit granting. Depending on the fact that education and occupation level have also been linked to level of income, these variables have been taken into account for almost entire systems. Hence, significant number of research have associated individuals’ socioeconomic background to their financial behaviour and level of debt. For instance, employment status, occupation, home ownership status, education, education of spouse, net wealth, income /

salary / income pattern / family income, length of employment and socioeconomic status (occupational / social class) have been used for building credit risk models.

Dessart and Kuylen (1986) reported that income, home ownership, length of employment, income pattern and some other indicators of socioeconomic status such as ownership of expensive durables and amount of financial reserves are significantly related with problematic debt. Harrison and Chudry (2011) examined the impact of social class, Ottaviani and Vandone (2011) considered wealth, income, employment status and education. L. Wang et al., (2011) discovered that social class and income are correlated of debt accumulation. Acquah and Addo (2011) revealed that debt repayment behaviour could be uniquely determined by education, income and length of employment. Xiao et al. (2011) stated that outstanding debt levels was significantly correlated with the parents' socioeconomic status of students. S. Costa (2012) discovered significance of wealth, income, household status, education and employment status, and von Stumm et al. (2013) emphasized the importance of education and income in predicting probability of bankruptcy. Brown and Taylor (2014) associated problematic debt levels with education and income as well. H. A. Abdou et al. (2016) examined occupation, education, length of occupation, previous occupation, number of dependents and home ownership and interestingly, length of previous occupation is incorporated into credit risk models, as a result of significance results.

2.1.6 Institutional / Financial Factors

For the last few decades credit granting decisions have mostly depended on the financial history (Wei et al., 2015). San Pedro et al. (2015: 195) stated that credit scores were traditionally computed from financial history of borrowers, which caused potential borrowers who do not have recorded financial history to be out of the credit system. Financial history of applicants are gathered by credit bureaus at some countries so as to present to the interested parties. Bureaus such as Experian and Equifax provide aggregated information regarding the past financial behaviour of applicants from a wide range of financial institutions (San Pedro et al., 2015: 195). Information from credit bureaus is considered as a reliable source by lenders, which caused lenders to have a tendency of selling credit products to the existing customers and customers who have financial history (Mester, 1997, as cited in San Pedro et al., 2015: 195). Potential borrowers excluded from the system is categorised as no-file or thin-file customers (San Pedro et al., 2015: 195).

In parallel with real world applications, remarkable number of research included financial predictors as well or solely emphasized financial factors in model development for probability of default. Among institutional variables examined, Dessart and Kuylen (1986) discovered that number of outstanding credits and credit score of the applicant are significantly associated with problematic debt. L. Wang, Malhotra and Lu (2014) studied problematic debt behaviour of Chinese bank customers based on demographical and financial indicators. Outstanding level of debt was positively correlated with the length of credit card ownership, credit card expenditure and credit limit. Female and younger customers demonstrated significantly higher amount of debt.

2.1.7 Alternative Factors

Credit scoring models emerged for evaluating risk assessment regarding the probability of default of credit borrowers. Over a long period, those models and the techniques they apply have evolved. Parameters considered for the risk assessment process and the data sources that they integrate have altered as well depending on the technological, cultural and economic changes. Growing credit market and significant number of enhancement in credit demand necessitated seeking new ways of scoring. Especially, in the case of lack of enough historical data to assess applications alternative data sources are considered recently. Ntwiga and Weke (2016) reported that social media data as a kind of an alternative resource of data in the case of scoring the applicants without financial history or having limited information for the assessment process. This kind of data provides enlargement of the parameter set or offers signals of personality, attitudes, values and behaviour of the applicants, which are remarkably important for revealing the financial, money management, credit repayment capabilities of borrowers.

Online peer-to-peer (P2P) lending refers to a relatively new business model serves as a digital platform which offers electronic commerce credit. Through an online platform lenders' and borrowers' processes regarding the credit applications and screening are performed instantaneously (Zhang et al., 2016: 168).

This business model offers the opportunity of accessing financial in an easier manner and without experiencing banks' burdensome screening processes. However, this process owns higher risks for lenders as a result of information asymmetry between lenders and applicant (Stiglitz, 1981, as cited in Zhang et al., 2016: 168). Online markets require credit scoring mechanisms to deal with this issue and behaviour characteristics of borrowers should be captured by the relevant indicators. This trend and the growing market also contributed to the investigations for different indicators and robust architectures for dealing with digital data. Zhang et al., (2016: 169) stated that people's social behaviour and words for communication can reflect the truth regarding their behaviour. Depending on this idea, researchers utilised social media data for a credit scoring decision support system and behavioural factors extracted from social media data are incorporated into conventional credit scoring. Researchers used some traditional factors such as age, gender, loan amount, credit score and proportion of failed and successful previous credit application in addition to factors derived from social media including social network prestige, contribution, network belonging score. A dataset including online loan applicants data is used to predict probability of default based on Decision Trees (Zhang et al., 2016). As a result, it was discovered that model had a good prediction capability compared to Neural Networks and Logistic Regression (Zhang et al., 2016: 174).

Blumenstock et al. (2015: 1075) studied on the comparison of digital indicators of wealth and individuals' actual socioeconomic status so as to propose how credit granting decisions can be supported in case of lack of data. Wealth index computed from a wide range of metrics extracted from mobile phone logs compared with the actual wealth index of individuals. Model's performance in terms of predicting individuals' socioeconomic profile accurately was efficient. Simumba, Okami, and Kohtake (2017) studied on the usage of alternative data particularly mobile phone data for improving the credit decisions. They obtained data from a mobile platform regarding the farmers who had loan requests. As the country of the study was Cambodia representing a great number of citizens, which live below poverty segment, applying mobile phone data increased the accessibility of loan for the unbanked poor. Thus, consideration of an alternative set of parameters for loan granting decisions contributed to the literature in terms of revealing new factors to be considered for evaluating the repayment ability of credit borrowers. San Pedro et al. (2015: 195) also utilised mobile phone data in order to capture personality and socioeconomic status indicators for facilitating decision supports associated with credit granting.

Huo et al. (2017: 246) utilised 23 variables based on borrowers’ daily communication behaviours. Behavioural characteristic of mobile phone users are extracted from digital signals such as number of friends communicated, online duration, IS registration name, other services’ utilisation, number of days of communication, number of friends communicated (outer), monthly payments, times of international moving around, amount of overdue payments, times of overdue payments and online & offline durations. Wang et al. (2013) utilised a dataset from a B2B e-commerce platform to predict probability of default. Variables considered include customers’ general behaviour such as frequency of connecting to the trading platform, behaviour regarding the transactions and data that is static comprising type, year and product of TP (credit granting program).

Wei et al. (2015) studied on network-based credit risk assessment for evaluating whether network-based data contributes to improve credit granting decisions. Depending on the fact that, people have a tendency of establishing ties with others like them they aimed to support credit scoring data with this network-based information. This kind of information aids in gaining insight into social status of people. Researchers stated that their model and utilisation of social network data reduces information asymmetries between lenders and applicants (Wei et al., 2015: 3).

Björkegren and Grissen (2018a) studied behaviour reflected and explored through mobile phone utilization patterns of loan borrowers. Researchers conducted the study in a developing country context and achieved excellent results in terms of scoring people with limited financial history. Traditionally, those people are considered out of the financial system as they did not establish any relationship with a bank or were not able to represent proof for financial data. Some mobile phone data variables considered for the decision support models for credit scoring were top up behaviour, mobility, handset utilisation behaviour and structure of network connections. Masyutin (2015) considered number of days since last visit, number of posts including photos or video, life style (quality of people around the user, major activities and believes in life) and number of subscriptions as social network variables for credit risk assessment.

Masyutin (2015) studied on estimating probability of default of individuals based on their social network profiles. They utilised Vkontakte profiles (Russian Social Network) and parameters comprising pattern of visiting the profile, number of posts including user's photos or video, major activities / interests / people in their life and characteristics of people in their network. Recently, better solutions for anticipating financial behaviour such as the effect of homophily, and trust signalling have been investigated by researchers (Galak et al., 2011; Herzenstein et al., 2011; Lin et al., 2013, as cited in Wei et al., 2015: 3). One probable negative outcome of social scoring emerges from widespread usage of this data in the future. People knowing that their social network and connections will impact on their credit score, they may develop their network in a more selective manner so as to reflect a socially desirable profile. Hence, this may lead to social fragmentation and coming to existence of socially undesirable individuals (Wei et al., 2015: 16).

2.1.8 Macroeconomic Factors

Depending on the fact that general economic conditions have remarkable impact on the probability of default of individuals, an important research stream has investigated the effects on default status on default. Some studies approached the debt repayment and default estimation from macro level perspective by incorporating macroeconomic factors into credit risk assessment models. Some indicators affecting probability of default at macro level comprise of unemployment rate, interest rate, changes in legal frameworks and divorce rate (Chakravarty and Rhee, 1999: 4). Meng, Hoang and Siriwardana (2013) examined the influence of population, interest rate, inflation, unemployment rate, GDP and consumer price index, and explored that interest rate, inflation, GDP, unemployment rate and population were unique predictors of level of debt among households. Oni, Oladele and Oyewole (2005), and Baek and Hong (2004) investigated interest rate as well. Chen and Wiederspan (2014) incorporated state finance policies, Cubiles-De-La-Vega et al. (2013) integrated nine macroeconomic indicators for predicting probability of default. Avery et al. (2004) integrated unemployment rate and census track's income (based on applicants residence) into credit risk model. Average bankruptcy filling rates, change in income, standard deviation of income, changes in bankruptcy filling and some state specific macro indicators are also examined as macro indicators influencing probability of bankruptcy (Chakravarty and Rhee, 1999; Fay, Hurst and White, 2002).

2.1.9 Health Related Factors

Investigation of health associated characteristics is limited by a few research in the relevant field which examined high risk driving and sexual attitudes, usage of drugs, high body mass index / obesity, inadequate physical exercise and bad nutrition habits (Berg et al., 2010). Yilmazer and Devaney (2005), and Webley and Nyhus (1998) integrated health status indicator for assessment of problematic debt levels, Norvilitis et al. (2006), Brown and Taylor (2014) and Nelson et al., (2008) considered overall stress, stress management and perceived stress. Santiago et al. (2011) explored that poverty related stress is correlate of delinquent behaviour. Nelson et al., (2008) examined some risk indicators for health such as body mass, weight control behaviours, sedentary behaviour, body satisfaction, dietary patterns and physical activity. Pirog and Roberts (2007) investigated body focus of participants and its relationship with credit misuse. Nurcan and Bicakova (2010) investigated the relationship between debt repayment and smoking. Indicator of depressive symptoms is explored as negative and significant determinant of indebtedness (Hojman, Miranda and Ruiz-Tagle, 2016). Vieira, de Oliveira and Kunkel (2016) explored that ill-being perception representing physical problems and depressive feelings was positively linked with positive financial behaviour.

2.1.10 Educational Factors

Defaulters demonstrate some particular attitudes and behaviour and they have different perceptions regarding money, credit and debt, which may be partly responsible for default. Hence, this dissertation considers the concept of credit risk assessment in a rather broader way by taking young adults and students into account as well. Thus, some evidence to propose prevalence, correlates and associations of problematic debt among young adults including students is valuable. A stream of research has concentrated on credit risk models for student loan. Consequently, some specific and context related factors are incorporated into credit risk models. These factors included GPA, field of study / major, year at school, number of educational debts, scholarship aid / other aid, graduation, class rank, type of school, high school education completion, academic experiences, highest college degree achieved, whether financial course was taken and some other institution related factors (Norvilitis, Szablicki and Wilson, 2003; Norvilitis et al., 2006; Nelson et al., 2008; Berg et al., 2010; Ismail, 2011; Chen and Wiederspan, 2014b; Akben-Selcuk, 2015). Smith (2011) and Norvilitis and Batt (2016) examined education specific factors for constructing credit risk models as well.

2.2 Literature Findings

Regarding the socioeconomic and demographic variables, Dessart and Kuylen (1986) reported that income, family life cycle stage, home ownership, marital status, number of bank accounts, length of employment, income pattern and some other indicators of socioeconomic status such as ownership of expensive durables and amount of financial reserves are significantly related with problematic debt. Costa (2012) focused on some socioeconomic, demographic, financial and situational factors for predicting probability of default of Portuguese households by means of Logistic Regression. Income, expenditure, level of debt, employment status, household characteristics (family life cycle stage & number of children), education and adverse life events are found significantly linked with default status. Strong evidence acquired regarding the impact of adverse life events on default status. A considerable percentage of households reported to experience an adverse circumstance in their life within the year prior to survey (Costa, 2012: 14). Domowitz and Sartain (1999) proposed a logit model for estimating probability of bankruptcy based on socioeconomic, demographic and financial variables. Among independent variables including homeownership status, debt to income ratio (for different types of debt), marital status, existence of other debts and debt to asset ratio, medical debt and credit card debt are significant correlates of probability of bankruptcy. In addition, debt to income ratio and home ownership status are significantly associated with the outcome variable.

Hira (1990) examined the problematic debt situation among 404 households in Scotland. The study was longitudinal with encompassing the years between 1984 and 1987. Gender, household size, employment status, marital status, sources of income, income, total debt, number of sources of borrowing, amount of debt from each debtor and total monthly debt of borrowers are investigated with regard to their link with the problematic debt. Number of sources of borrowing and household size increased by the level of debt. In addition being male and married had significant correlation with the dependent variable. Gardner and Mills (1989) investigated some loan characteristics, demographic, socioeconomic, financial and situational variables with regard to their correlation with probability of default. Borrowers having previous default and having less stable income were more likely to default. Property location and some loan characteristics like loan-to-value ratio were significant correlates of default. He et al. (2016) worked on defining profile of borrowers with outstanding credit card balance. Heckman procedure for coping with feature selection in the case of small sample size and imbalanced data is utilised. Based on findings, age, home ownership status, occupational industry and amount of cash advance were significant correlates of outstanding debt. Dessart and Kuylen (1986) examined the relationship of a wide set of psychological, decision making, institutional and socioeconomic factors with the level of problematic debt. Bivariate analyses indicated that external locus of control, time orientation (future/past), financial knowledge, viewing financial management important and deferring satisfaction were significant correlates of problematic debt.

J. Wang and Xiao (2009: 2) studied on predicting the antecedents of over indebtedness by considering compulsive buying, income pattern, social support for debt, gender and impulse buying factors. It is explored that over-indebted individuals were more likely to be compulsive buyers and those who have budget constraints. In sufficient social support might result in problematic financial behaviour and social support is found as a negative predictor of indebtedness. Parental guidance, involvement, communication and guidance are considered within the social support context. Ding, Chang and Liu (2009) studied on the repayment behaviour and specifically intention of not to repay of credit cards holders in Taiwan. Specifically, personality and behavioural indicators are focused. External locus of control and general ethical judgements were significantly predicted intention to not repay. Simmons (2013) investigated the relationship between mental health and debt by reviewing the associated literature. Compulsive buying tendencies, parents' behaviour in terms of mentoring and financial guidance, depression, anxiety, stress, problems in marriage, smoking, drinking, sedentary behaviour are mentioned as the correlated of amount of debt by the literature. Omar et al. (2014) examined credit misuse among credit card users in Malaysia by focusing on personality and behavioural factors. Self-esteem, materialism, impulsiveness and compulsive buying of participants are investigated. Findings demonstrated that self-esteem is found to be a negative and significant determinant of credit misuse whereas compulsive buying is positively linked with the compulsive buying.

Stone and Maury (2006) proposed a multi-disciplinary behavioural model by incorporating behavioural, situational variables in addition to traditional economic and demographical factors to predict indebtedness. Predictive capability of Logistic Regression model powerful and likelihood ratio tests revealed that indebtedness phenomenon was a multifaceted issue including demographical, socioeconomic, personality, behavioural and situational elements. Life altering events in the last 12 months representing situational variables and money beliefs and behaviours had uniquely contributed to explanation of outstanding level of debt. Tokunaga's (1993) study is also one of the prior studies that embarked on multidisciplinary approach to credit risk assessment. Tokunaga (1993) prosed an integrative model specifically focusing on psychological variables to reveal the profile of credit misusers. It is discovered that psychological variables enhanced the predictive capability of the model by categorizing successful and unsuccessful credit users accurately. External locus of control, attitudes towards money_power & prestige, anxiety about financials and parents' credit attitudes_positive were positive correlates of credit misuse. Parameters of self-efficacy, attitudes towards money_retention, risk taking, sensation seeking and number of credits utilised uniquely predicted credit misuse as well. One comprehensive study in the literature that incorporated various types of indicators is the research of Rogers et al. (2015). Researchers put emphasis on the contribution of behavioural and psychological variables for construction of probability of default models. Experiencing adverse life events, compulsive buying, viewing consuming behaviour as necessity, drinking behaviour (proxy for self-control), self-efficacy are significantly and positive associated with probability of default. In order to assess money attitudes Meaning of Money Scale with eight dimensions are utilised. Findings revealed that suffering, inequality and conflict dimensions representing individuals view of aspect with regard to money is positively linked with the default status. Marital status, number of credit cards, home ownership status and education of spouse were also among significant determinants of default behaviour.

Donnelly, Iyer and Howell (2012) examined sense of financial responsibility based on age, gender, education and Big Five personality traits. Within the scope of the same research another analysis is conducted as well by focusing solely on personality and behavioural indicators. The first study revealed that education and conscientiousness are positively, and significantly linked with the positive financial behaviour whereas individuals with high level of neuroticism and extraversion exhibited more irresponsible financial behaviour. The other study employing different parameters on a different sample revealed that materialism is inversely correlated with positive financial behaviour. Conscientiousness is again determine the difference in the outcome variable uniquely, with being positive correlates along with the agreeableness. Further analysis also revealed that people with low money management skills are more likely to accumulate high amount of debt.

Zhu and Meeks (1994) studied on the low-income families by examining problematic / outstanding debt based on variables comprising age, attitudes towards credit, outstanding credit balance in the past, education, employment status. One of this early studies conducted at the beginning of 1990s reflected that credit decisions in addition to demographical, socioeconomic and financial commenced including behavioural factors for decision making. von Stumm et al. (2013) proposed a model for predicting negative financial behaviour based on behavioural and some socioeconomic variables. Financial capabilities such as making ends meet, planning ahead, keeping track and staying informed were significant, and the most influential correlates of adverse financial events. Lea et al. (1995) also examined the influence of psychological variables on financial behaviour. Social support for debt, social comparisons, poor money management skills and some lifestyle indicators are found significant correlates of problematic debt. Besides, participants with high level of had less number of money management facilities and shorter time horizon.

Santiago et al. (2011) examined the influence of socioeconomic status, income, stress and neighbourhood disadvantage on the psychological problems including delinquent behaviour. Except age, all factors are found positively correlated with the probability of delinquency in a low income multi-ethnic sample in U.S. Strong evidence have demonstrated that socioeconomic status and low income cause unfavourable consequences by constituting constraint on financial resources and chance for higher income. Further, these individuals are more likely to encounter adverse life events and bad situations (Ennis, Hobfoll and Schroder, 2000, as cited in Santiago et al., 2011: 219). Living in a poor neighbourhood means being exposed to more stressors and deteriorating circumstances which in turn impacts on the psychopathology levels of individuals. Thus, examining socioeconomic status and neighbourhood disadvantage in conjunction may operate differently in the role of probability of delinquent behaviour (Santiago et al., 2011: 227).

Link between outstanding debt and criminal behaviour is reported by numerous studies. Merton and Agnew associated criminal behaviour with strain. Merton's theory clarifies crime as the result of conflict between desires and favourable circumstances and expectations to meet those desires / requirements legally. This theory principally refers to people with low level of socioeconomic status with lower financial resources and chances to achieve their goals. The theory assumed that the criminal behaviour may emerge from the strain stemming from being in between desires and opportunities to meet those desires. Hence, financial problems and limited fulfilment of material goals may cause delinquent behaviour. Thus, the level of debt and financial problems increase the risk of delinquency in terms of loan repayment (Hoeve et al., 2014: 2).

Acquah and Addo (2011) examined loan repayment performance of fisherman based on Multiple Regressions analysis. In addition to classical variables including age, education, income and loan amount, duration of the employment and loan processing matters are taken into account. Income, education and duration of the employment are positively, and significantly correlated with the loan repayment performance, whereas loan amount and age of the borrower are negatively associated. Berg et al. (2010) depending on the idea engagement in risky health behaviours and outstanding debt are related with very much alike psychological measures, investigated the level of debt among college students based on health related factors comprising smoking, high-risk drinking, drinking, physical activity and mental health. A set of demographical parameters such as age, gender and type of school was examined as well. Using Logistics Regression results demonstrated that smoking and drinking are positively associated with high levels of debt. Lack of physical activity and poor mental health had a significant correlation as well. Age, gender and type of school were other significant variables that proved correlation with the outcome variable.

D'Alessio and Lezzi (2013) mentioned financial imprudence, poor financial management, financial literacy and decision making style as drivers of over-indebtedness.

Financial imprudence is associated with decision making without thinking its consequences and underestimating actual cost of borrowing. Unexpected life events or life altering events might also affect over-indebtedness. For instance, fluctuations in income, unexpected health expenses, marriage or death of a family member are considered among life events. Mewse et al. (2010: 1021-1034) incorporated financial, demographical, socioeconomic and some personality factors for prediction of profile of individuals with high level of debt. Analysis was performed on a sample drawn from general population in U.K. and findings indicated that difference in debt levels could be explained by personality factors including optimism, self-esteem and locus of control. All three variables were negative and significant correlates of level of outstanding debt. Those whose home ownership status was rent and unemployed were more likely to accumulate higher amount of debt. Seeking advice from other, number of children and age were also other determinants of outstanding debt levels.

Strömbäck et al. (2017) conducted an investigation on the psychological influencers of positive financial behaviour for gaining better insight into financial decision making process of individuals. Thus, in addition to age, gender, income and education, some specific personality and behavioural factors such as self-control, financial literacy, optimism and deliberative thinking are examined with regard to their influence on the positive financial behaviour. The empirical study performed on 2063 Swedish sample indicated that self-control, financial literacy, optimism and deliberative thinking are positively linked with the positive financial behaviour. Those with high level of income, female and at older ages were also more likely to exhibit positive financial behaviour.

Chakravarty and Rhee (1999) studied on estimating probability of default based some socioeconomic, demographic, financial, situational and macroeconomic indicators through Multinomial Logistic Regression. Adverse life events as situational factors, wealth, age, ethnicity, marital status, length of employment, existence of problems regarding the money management in the past and income are explored as significant correlates of probability of default. Rutherford and Devaney (2009) discovered that credit misuse was positively and significantly correlated with holding positive attitudes towards credit utilisation, having less risk tolerant, utilisation of credit for vocational purposes, number of behind schedule payments, level of shopping, having financial credit advice from sources of media. Households educated from college, having longer time horizon and older were significantly responsible credit utilisation behaviour.

Particular personality factors are found significantly linked by the high levels of debt. For instance, low levels of self-control, self-esteem, perceived money management capabilities, perceived financial well-being and lack of money management capabilities are found as determinants of problematic debt. Individuals with low self-control levels exhibited poor saving behaviours and are prone to spend more money (Baumeister, 2002; Romal and Kaplan, 1995, as cited in Berg et al., 2010: 1). Some other psychological factors found related with problematic debt comprise delay of gratification, impulsiveness, short-term thinking, ignorance of long- term consequences and self-efficacy (Berg et al., 2010: 2).

At 1980s, Godwin (1999) performed a longitudinal study for estimating probability of debt repayment difficulty of households in U.S. This study was one of the earliest studies that incorporated behavioural variables for examining default, and specific debt attitudes and behaviour are explored to be significantly correlated with repayment difficulty. For instance, those who approved for various uses of credit and previously rejected for credit application were more likely to have repayment difficulty. Having other forms of debt and household size are discovered as the positive correlates of the outcome variable whereas age is negatively linked. One important aspect of the study was the incorporation of the situational variables in the form of adverse life events, which revealed that existence of those kind of events increased the probability of experiencing repayment difficulty. Zainol et al. (2016) performed analysis for determining indebtedness behaviour among a sample having debt problems in Malaysia. Specifically, effect of psychological and attitudinal factors are considered and results indicated that extraversion, impulsiveness, neuroticism, parental guidance, religious principles and purchasing for lifestyle were significant determinants of indebtedness among the examined population. Brown, Garino, Taylor and Price (2005) investigated level of debt and growth in debt levels of households in U.K. based on age, gender, age, marital status, ethnicity, household status (size), number of children, financial expectations and vehicle ownership. Findings demonstrated that optimistic financial expectations and household size are positively linked with the level of debt, whereas value of the house owned was negatively correlated. Debt levels of married individuals and male households, were significantly less than the other participants'. Attitudes towards credit demonstrates willingness of applicants in terms of credit usage. The applicants evaluate appropriateness of credit utilisation considering questions about at what extent they support credit utilisation (Zhu and Meeks, 1994).

Chien and Devaney (2001) examined outstanding debt by investigating the influence of behavioural, financial, demographical and socioeconomic indicators. Variables comprising attitudes towards credit, income, assets, property ownership, age, household size, marital status, ethnicity and occupation arre examined with regard to their correlation with the outstanding credit balance. Based on empirical analysis of American households it is explored that marital status, occupation, home ownership, household size, education, income and attitudes towards credit are uniquely predicted probability of outstanding debt. Yilmazer and DeVaney (2005) demonstrated that income, existence of financial assets, age, marital status, education, gender, ethnicity, risk tolerance and employment status were exhibited significant relationship with the level of debt. In addition having poor health status is negatively linked with the level of debt. Households who reported high level of risk tolerance were more likely to carry greater levels of debt whereas self-employed individuals' debt amount was significantly lower. Also, being female and graduate from a college had negative relationship with the dependent variable. L. Wang, Lu and Malhotra (2011) proposed a model for predicting credit card behaviour. Study is based on the investigation of demographical, behavioural, personality and some financial variables. Based on analysis results, demographical and other variables except from behavioural and personality factors had inadequate explanatory power. Specifically, self-control, self-esteem, internal locus of control, attitudes towards credit, money attitudes, attitudes towards credit, deferring gratification, self-efficacy are found to be significant determinants of level of debt. Particularly, power & prestige and retention dimensions of money attitudes were significant correlates. Participants with lower levels of self-control, from low social class, having external locus of control and positive attitudes towards debt had higher levels of debt. Number of credit cards and credit limit are positively associated with level of debt.

Financial decision making of individuals from the aspect of problematic debt is approached from psychological perspective by Brown and Taylor (2014), as well. Personality traits included within the Big Five taxonomy and perceived health status of households are assessed with regard to their correlation with different types of debt. Certain traits are significantly correlated with level of debt of households. Extraversion and openness to experience are positively linked with the level of debt whereas age, education and perceived health status were negative correlates of the outcome variable. Other dimensions of Big Five are found insignificant. Nyhus and Webley (2001) discovered that autonomy, agreeableness, being meticulous, emotional stability, age and education uniquely predicted financial behaviour. Low level of emotional stability and high level of agreeableness and autonomy are associated with positive financial behaviour. Griffin and Husted (2015) explored that loan repayment behaviour is influenced by social relations and social sanctions in group lending of microfinance loans. Bryan et al. (2010) conducted a longitudinal survey to evaluate correlates of over-indebtedness and characteristics of individuals who are over-indebted. Younger ages, home ownership status_tenant, low income, unemployment are found associated with over-indebtedness. Attitudes towards debt, attitudes towards money, spending and behaviour are also found significantly linked with over-indebtedness. Ganzach and Amar (2017) investigated some socioeconomic and personality indicators comprising financial resources, income, parents' income, intelligence and Big Five personality traits. Intelligence, income, worth of resources and income of parents are significantly predicted debt repayment difficulty. Among Big Five traits conscientiousness is positively linked with the repayment difficulty whereas neuroticism positively contributed to the explanation of the outcome variables.

Oni et al. (2005) examined probability of default of farmers in Nigeria based on probit regression analysis. Among demographic, socioeconomic, macroeconomic and financial variables investigated age, education and income is found as significant determinants of default. Excessive amount of debt is associated with various factors including irrational consumer behaviour, which is provoked by credit products and retailers' advertisements, and over-confidence in future financial expectations. Other behavioural determinants includes consumption life-style, impulsiveness, financial literacy and self-control problems. Social pressure and its influence on consumption inclination can explain over-indebtedness as well (MFC, 2014). H. A. Abdou et al. (2016) utilised demographic, socioeconomic and some financial variables including loan characteristics, expenditure, existing credits, age, gender, marital status, education, occupation, previous occupation. Among variables considered accounts' functioning status, existing credits, expenditure, existence of guarantees and previous employment's duration are found as significant indicators of probability of default. These variables, therefore are utilised for the knowledge-based model construction. Bernerth et al. (2012) offered a credit risk evaluation system based on some demographical, behavioural and personality factors. Probability of default behaviour based on actual credit scores (FICO) is examined. Big Five personality measure, job performance and education of a sample drawn from employees of a particular university in U.S. Conscientiousness is positively linked with credit score while agreeableness is negatively correlated. Results regarding the other dimensions of Big Five were not significant.

The study of Ottaviani and Vandone (2011) indicated that participants with high level of impulsiveness had significantly higher amount of debt. Gambling task score which represented different decision making styles under uncertainty was also significant determinant of the outcome variable. Unemployed participants and participants with more children held significantly higher amount of debt. Self-reported wealth was also indicator of level of debt. Kim and DeVaney (2001) conducted a theoretical analysis regarding the behaviour of credit card users. Researchers reviewed prior studies to reveal antecedents of problematic / outstanding credit card balances. Socioeconomic, demographical, financial and some behavioural parameters are examined to explore correlates of problematic / outstanding debt. Specifically, time horizon, attitudes towards credit / use of credit, income expectation, assets, credit limit and behind schedule payments are examined in addition to commonly included demographical variables. Having time horizon more than 5 years, amount of assets, education, income and credit limit are negatively, and significantly linked with the problematic debt behaviour. On the other hand, parameters of positive attitudes towards credit, behind schedule payments, interest, number of credit cards and some specific purposes for credit utilisation are represented positive correlation with the outcome variable. Livingstone and Lunt (1992: 114) indicated that explanation of debt and repayment problems should be interdisciplinary with encompassing social science disciplines. Economics deal with the influence of income and consumption patterns in conjunction with the life cycle theory. Sociology approaches the phenomenon from the aspect of social groups and evaluates social norms. Social psychology puts emphasis on individuals' locus of control and attitudinal factors. However, earlier studies did not incorporate different aspects for explanation of repayment behaviour. The study of Livingstone and Lunt (1992) is one of the exceptional studies that approached the debt and debt repayment phenomenon from multi-disciplinary perspective by considering psychological, socioeconomic and behavioural perspectives. Among demographic variables social class and partner's social class, and among economic variables income and number of debts were significant. Locus of control, coping strategies, economic behaviour in terms of consuming, credit attitudes, number of debt and bank accounts are included in the final model for prediction of amount of debt. Ethnicity, age, marital status, income, home ownership, gender, education, household size, employment status, socioeconomic status, number of children, financial situation, family income, unemployment status of spouse, family life cycle status, net wealth, length of employment, occupation (Gray, 1985; Dessart and Kuylen, 1986; Wilms, Moore and Bolus, 1987; Greene, 1989; Hira, 1990; Livingstone and Lunt, 1992; Tokunaga, 1993; Ryan, 1993; Dynarski, 1994; Zhu and Meeks, 1994; Davies and Lea, 1995; S. E. G. Lea et al., 1995; Baek and Hong, 2004; Yılmazer and DeVaney, 2005; Sustersic, Mramor and Zupan, 2009; Mewse, Lea and Wrapson, 2010; Ottaviani and Vandone, 2011; Acquah and Addo, 2011; Gathergood, 2012; S. Costa, 2012; Limerick and Peltier, 2014; H. A. Abdou et al., 2016) are widely utilised in building credit scoring models.

2.2.1 Literature Findings for Student Related Studies

Young adults of the century have very easy access to credit in some so-called credit cultures such as U.S. particularly since the beginning of 2000s. However, moderate level of increase in financials and prevalence of credit offerings caused young adults' vulnerability, which impacted on increasing levels of indebtedness (Dwyer, McCloud and Hodson, 2011: 728). Recently, debt and financial problems of young adults over 18 have enhanced. Prevalent usage of credit cards, increase in spending with credit card, university expenses and changing trends in the field of consumer borrowing and financial behaviour have impacted on young people as well (Hoeve et al., 2014: 1). Credit utilisation is a requirement for young adults and students of today due to increase in requirements, high costs of education and associated costs. However, lack of financial history and provable past payment behaviour are barriers in front of credit access for young people.

In addition, depending on the fact that defaulters tend to exhibit specific attitudes and behaviours and stereotype profiling of defaulters can be captured by means of examining different sample characteristics. Therefore, research associated with young adults or students make contribution to profiling of defaulters. Regarding the students' characteristics determining probability of default, some consistent findings of the relevant literature demonstrated significant link with income, loan amount and family size (Dynarski, 1994: 66). Robb (2011) considered socioeconomic, demographic, educational and behavioural factors so as to estimate credit misuse of college students in U.S. Financial knowledge of students is negatively correlated with credit misuse, whereas financial independence, having financial aid and number of debts are positively linked with the outcome variable. Norvilitis (2014) examined correlates of debt levels among a sample drawn from U.S. college students. Number of credit cards and income are found as positive correlates of level of debt whereas perceived financial well-being and delay of gratification are negatively linked with the independent variable.

Chen and Wiederspan (2014) investigated the problematic debt behaviour from a different view of aspect by focusing on institutional and state related macro indicators for prediction of repayment difficulty. Students at public institutions and at particular programs of study demonstrated significantly higher level of debt whereas students from high income families had significantly lower debt levels (debt-to-income ratio). Davies and Lea (1995) discovered that debtors had more number of credit cards, had positive attitudes towards debt, older and male. Some categories of religion are found correlated with high amount of debt as well. Interestingly, some examined variables did not demonstrate significant relationship with the level of debt such as locus of control, expenditure, adverse life events and income, which is correlated with some problematic issues in the scales utilised. Akben-Selcuk (2015) indicated that financial behaviour could be determined by financial literacy, money attitudes, gender, parental instructions and whether a financial course is taken based on empirical analysis of a sample comprising college students in Turkey. Parental instructions, financial literacy and positive money attitudes are positively related with the responsible financial behaviour.

Limbu (2017) examined the effects of social motivation, credit card knowledge and self-efficacy of students on credit misuse. Credit card knowledge and social motivation are negatively and significantly associated with credit misuse. Sidoti and Devasagayam (2010) utilised behavioural indicators comprising risk attitudes, materialism & money spending and the effect of credit cards vendors on credit misuse behaviour. Entire parameters are accepted as significant indicators of irresponsible credit behaviour. Marketing strategies and gifts for distributing credit cards determined credit misuse. Risk taking attitude and possession of materialistic values had uniquely determined the misuse behaviour among student sample. Norvilitis and MacLean (2010) specifically focused on the parents' role on the economic socialisation of students by examining the influence of parental guidance and parental instructions on the level of debt. In addition, perceived financial well-being, knowledge and delay of gratification are examined with regard to their correlation with credit misuse and level of debt. Level of debt is significantly and positively related with the problematic credit card utilisation while it was negatively linked with perceived parental bailout, financial well-being and parental facilitation. It is explored that delay of gratification, parental bailout and facilitation were negatively associated with the level of debt. Hancock et al. (2013) proposed a model for estimating credit card behaviour of students. Parental influence, attitudes towards credit cards, financial knowledge, gender, work experience and parents' income are incorporated in a Logistics Regression Model. Number of credit cards and outstanding debt levels are significantly related with parental influences, attitudes towards credit cards such as making minimum payments on credit card debt.

Norvilitis et al. (2003) examined the level of debt of American college students. Contrast to previous studies, this study did not explore correlation between personality factors comprising locus of control and impulsivity and level of debt. Perceived financial well-being is negatively linked with the outcome variable. Brougham et al. (2011) examined debt repayment behaviour for focusing psychological aspects. In addition to some socioeconomic variables, money management, financial knowledge, emotional stability, materialism, financial behaviour, financial anxiety, introversion and future time perspective are included in prediction models. Emotional stability and responsible financial behaviour variables exhibited strong negative association with problematic debt repayment behaviour, whereas materialism is found to be positively linked. The study of Gray (1985) is one of the earliest studies in student loan default. In addition to general socioeconomic and demographic indicators, institutional and educational variables including GPA, field of study, number of educational or other debts are examined. Number of debts, field of study, marital status, ethnicity, GPA and family income are uniquely predicted default behaviour of American students.

General theory of crime associates crime with lack of self-control and deficiency in developing self-control during mid-childhood due to a wide range of factors including parenting style. Lack of self-control is not only associated with criminal behaviour, it is also closely linked with a wide range of risky behaviours stemming from instantaneous gratification. Thus, connection with one of risky behaviours will probably enhance the risk of engagement in other problematic behaviours (Hoeve et al., 2014: 2). Thus, several studies have examined self-control problems and behaviours associated with lack of self-control with regard to their correlation with loan delinquency. Empirical studies specific to debt of students and/or young adults also linked debt repayment or problematic debt with parental factors such as parental instruction, social pressure and parents attitudes towards debt (Hoeve et al., 2014: 2).

Gross, Cekic, Hossler and Hillman (2009) worked on probability of default of student loan and conducted a systematic review of indicators of student loan default. According to review institutional characteristics including proprietary or less than four year colleges, ethnicity, age, gender, socioeconomic background, parental factors, income, amount of debt, academic achievements, educational attainment, prior academic success (high school related success factors), major (program of study) and attitudes towards debt were among determinants of student loan default (Gross et al., 2009). Hoeve et al. (2014) investigated problematic / outstanding debt among young adults. Age, gender, ethnicity are found significant correlates of debt. Positive and supportive attitudes towards debt, low level of self-esteem, external locus of control and lack of self-reported control over financial managements are also strongly linked with problematic debt. Seaward, Hamish and Kemp (2000) investigated the effect of over-optimism on indebtedness on a sample comprising students. Underestimation of time that encompasses repayment period and overestimating the future income means being over-optimistic about debt repayment capability which might result in indebtedness. Study of Seaward et al. (2000: 19) revealed that financial optimism is significantly associated with the level of debt.

Many studies reported that as students get older, probability of default increases. Regarding the gender, results are contradictory and demonstrates mixed findings. Family structure is important and as the number of dependents increase probability of default increase as well. In addition, life events such as divorce, separation and being widowed or single parent are closely linked with default. Education of parents significantly reduces the default risk and students from low-income families are more prone to default. Academic achievements and educational attainment are found as the most powerful factors predicting loan default. Academic experiences in high school is also correlated with default status. Even though the explanation behind the matter was not clear enough, program of study was among factors that signals higher risk for default (Gross et al., 2009). Ryan (1993) focused on university students and probability of default of educational loans. Examined variables included demographical, socioeconomic, educational and behavioural variables. The category of educational in this case is associated with some institutional and individual characteristics of students related with their academic study. Utilisation of financial aid, family income, current employment's consistence with the major, GPA and credit knowledge (rights & responsibilities) were among significant determinants of probability of default.

Ismail, Serguieva and Singh (2011) investigated education loan repayment behaviour. Socioeconomic, demographic, financial, and behavioural and some education related variables are examined. Attitudes towards loan repayment, perceptions towards loan agreement and awareness of loan repayment are explored as significant positive correlates of positive debt repayment behaviour. In addition, parents' instructions and guidance are positively linked with repayment behaviour. Moreover, students' beliefs regarding the repayment will impact their life quality in after days was linked with their repayment. The relationship between students' attitudes towards loan repayment and intention to repay is found significantly associated as well (Ismail et al., 2011). Dynarski (1994) examined default behaviour of students based on a set of demographic, socioeconomic, financial and education related variables through a Logistic Regression Model. Among variables investigated income, ethnicity, type of school attended and whether high schools was completed or not had significant link with probability of default of students. Regarding the school type, borrowers had two-year college education or studied at proprietary schools demonstrated higher levels of default probability.

Greene (1989) examined university students’ loan repayment behaviour by estimating probability of default. Solely demographic and some financial variables are utilised for model construction. Grant aid and scholarship aid are positively linked with default, whereas GPA and income represented negative relationship with the independent variable. Moreover, graduates from high school demonstrated lower probability of default compared to those drop out. Wilms et al. (1987) worked on characteristics of students who defaulted on educational loans. In addition to classically examined demographic and socioeconomic factors, they examined some educational variables associated with institution and education of students. Variables of prior education, program of study, income, being enrolled in proprietary school, ethnicity and citizenship were among significant determinants of default behaviour.

Norvilitis et al. (2006) incorporated socioeconomic, educational, financial, personality and behavioural factors into regression models for predicting outstanding level of debt among college students. Number of credit cards, delay of gratification, age, overall stress and projected debt repayment period are positively correlated with level of debt. Those who had higher levels of financial knowledge and who were older had significantly lower amount of debt. One interesting finding of the study was that demographic variables except from age did not exhibit any significant relationship. Lyons (2004) discovered that students having high level of financial risk used financial aid and held high amount of debt. Gender and ethnicity are also among correlates of financial mismanagement. Xiao et al. (2011) used Theory of Planned Behaviour to explore risky credit behaviour of students. Researchers examined behavioural, personality and education related variables impact on credit misuse, level of debt and financial behaviour of students. Financial knowledge, parental norms, other norms, attitudes towards positive financial behaviour, self-efficacy and controllability were among some parameters examined. Positive financial behaviour is significantly linked with attitudes towards positive financial behaviour, self-efficacy, parental norms and controllability. Credit misuse is negatively correlated with positive financial behaviour and financial knowledge. In the case of outcome variable of outstanding debt, it is explored that risky credit behaviour is positively linked with outstanding amount of debt, whereas positive financial behaviour is negatively correlated. Parents' socioeconomic status also caused differences in financial behaviour as risky financial behaviour is negatively linked with parents' socioeconomic status.

Roberts and Jones (2001: 213) examined the act of attitudes towards money and credit utilisation on compulsive buying by investigating college students in U.S. Results revealed that power & prestige, anxiety and distrust dimensions of money attitudes are significantly associated with compulsive buying and credit utilisation was a moderating factor on this relationship. Fogel and Schneider (2011) estimated credit card misuse of college students in U.S. based on income and employment status. Full-time workers and students with high level of income exhibited significantly more irresponsible behaviour.

Overall this assessment provides some insight into students' credit utilisation behaviour, particularly who are at risk of default. Factors that have been investigated comprise prior education, field of study, family income, number of debts, program of study, citizenship, GPA, scholarship aid, grant aid, utilisation of financial aid, religion, high school education, number of credit cards, attitudes towards debt, perceived financial well-being, financial knowledge, delay of gratification, overall stress, money beliefs and behaviours, year at school, health related indicators, parental instructions and guidance, credit card misuse, compulsive buying, social support for debt, risk attitudes, smoking, drinking, physical activity, ethnicity, parents' education, extraversion, attitudes towards debt, money management, parents' socioeconomic status, emotional stability, conscientiousness, agreeableness, impulsiveness, locus of control, debt management and social motivation. These are factors that revealed statistically significant link with the outcome variables. However, among studies examined at most 18% of studies were longitudinal in nature and 85% of studies implemented in U.S. which prevents generalisability of results to different contexts.

2.2.2 Analysis of Findings

Determinants of consumer credit have been examined since the end of 1960s. The most prevalently utilised determinants have been sociodemographic and economic variables comprising education, income, household assets, family life cycle stage, marital status, gender, size of household and home ownership status. Research on attitudinal variables are limited with a few studies demonstrating low levels of significance. Nevertheless, before 1990s, studies in the field did not specifically consider the determinants of credit risk extensively and those studies were very general in nature (Zhu and Meeks, 1994: 405). Studies that approach credit use from the aspect of representation of the situation have mainly investigated the impact of socioeconomic and demographic factors on credit utilisation. Behavioural economics related approaches often concentrated on this aspect. Another aspect has regarded the credit utilisation as an individual matter, which is associated with personal attitudes towards money, credit use and personality factors. Another perspective has concentrated on the social dimension. This aspect has considered the effects of interdependencies of individuals from a sociological point of view. Impacts of social pressure and social norms are within the scope of this sociological point of view (Kamleitner et al., 2012: 3).

Establishment of the profile of people with credit associated problems are initially based on identifying demographic and socioeconomic profile of customers. A small body of research at that times focused on the attitudinal and behavioural aspects, and particular interest is paid to the capturing behavioural patterns through past financial history. Tokunaga (1993) reported that research on credit card utilisation and bankruptcy before 1990s had determined these groups of indicators; demographic, socioeconomic, situational (adverse life events) and some attitudinal limited attitudinal variables such as money beliefs and behaviours. Literature is lack of a comprehensive study that comprises an extensive list of socioeconomic, demographic, financial and institutional, personality, behavioural and situational indicators. In addition, there are many options for the definition of the outcome variable, which demonstrates probability of default and problematic debt. Thus, systematic review aimed to offer a framework for determining the alternative outcome variables and their association with the independent variables mentioned by the previous literature. Previous research revealed contradictory results regarding the stereotype of debtors.

Foresights regarding expansion in credit utilisation in the near future necessitates integration of cultural variances into the models for decision support for credit granting. Kamleitner et al. (2012: 21) indicated that geographical focus of the most studies in the literature is on U.S. and some particular European countries. Especially, studies handling the credit utilisation from cognitive perspective have been mostly conducted in these cultures. Further, with regard to social perspective some particular variables have been examined only for some particular cultures, which makes the findings inconclusive. Existence of cross-cultural studies is important in terms of examining cultural nuances and adjusting parameters within the cultural context. Kamleitner et al. (2012) stated that providing insight into global understanding could be provided by anticipating the cultural differences and similarities for borrowing processes. This requires large scale cross-national effort to incorporate social and cultural facets of the phenomenon. For instance, cross-cultural study of (Norvilitis and Mao, 2013) reported different money and credit attitudes between students in U.S. and China. Scientific research investigating correlated of debt and probability of default is rare when Western cultures are not taken into account.

Recently, vast studies concentrated on loan delinquency, repayment behaviour and probability of default. However, except from some particular patterns, findings of the studies are contradictory. Different methodologies have been applied to different set of parameters and feature selection methodologies that produced various combinations of variables. Samples usually are drawn from Western cultures and are not obtained in a randomized manner. Characteristics of good and bad repayment behaviour can change based on the lenders, institutions, cultures and governments' legal framework. Hence, set of parameters inputted for the models have extremely varied which prevented to uniformly define an industry standard credit risk assessment system. At some cases, secondary data have been utilised for construction of models. In this case, examined variables often depend on the dataset on hand. Nature of the credit evaluation and its multifaceted characteristics causes interdependencies and relations between predictor variables, which might result in confrontational results. According to H. A. Abdou and Pointon (2011: 67) in the case of constructing credit scoring models, existence of optimum number of parameters is not an accepted idea as the variables selected are closely linked with the environment, culture, economy and many other issues related with the market which the application focuses on. Besides, these parameters vary based on the country of the study. Thus, the process of defining the number of variables and the set of variables chosen to construct models for decision support is a multifaceted issue affected by technological drivers, trends, culture, economy and legal framework.

Characteristics utilised in credit scoring domain vary based on the situation. Loan type defines the type of the information taken into account for risk assessment. In addition, in some cases legislation defines the extent of variables to be considered as in some countries gender or ethnicity are not permissible by law (Hand and Henley, 1997: 526). Hand and Henley (1997: 524) mentioned some conventional characteristics including home status, telephone, age, loan purpose, time with bank, income, time at present address, time with employer and occupational status that are used for credit risk assessment (Hand and Henley, 1997: 527). Debt repayment, financial behaviour, credit use, problematic debt, outstanding debt, default has been extensively documented by the previous studies. Even though majority of results are based on work of Western scholars, some particular attention is put on the developing countries as well. However, there are still research gaps to address. A little number of research has taken into account different attitudinal characteristics at the same time. Some research considered only separate effects of certain variables instead of examining their joint effect. Results are not representative of a larger population. Prior studies focusing on the creditworthiness phenomenon from behavioural and psychological perspective have revealed unambiguous findings.

Šušteršič et al. (2009: 4737) reported that for the past studies worked on the model development for credit scoring, data is generally acquired from datasets of credit bureaus or credit unions and they included relatively limited number of parameters (5 to 20). Mostly these were the available parameters within the dataset or they are selected based on past experiences of the lenders. The limitation of this approach is that most researchers did not consider the variable selection process as an important stage in the case of model development. They also reported that highest number of variables explored in the literature was discovered in the study Jacobson and Roszbach (2009) (as cited in Šušteršič et al., 2009: 4737). However, systematic review conducted within the scope of this dissertation revealed that more recently larger set of variables considered for the model establishment. Dealing with larger set of variables is important and the recent global trend in the credit granting decisions is supporting decisions by large set of variables, as data is limited especially in the case of existence of applicants with limited credit history.

Number of variables considered for model construction is an arguable issue. As data sets are often extensive, overfitting problems may emerge. Hence, ways of utilising as many characteristics as can be investigated. However, this is not a practical approach in the case of implementation. Statistical methods, pattern recognition or feature extraction techniques facilitate to eliminate large number of characteristics into smaller set of variables that are closely related with the outcome variable. Expert knowledge can be used to find out predictive characteristics as well. However, in this case expert view is usually used for complementary knowledge regarding the statistical analysis. Stepwise statistical approaches are another method for variable selection. Forward stepwise technique sequentially add parameters, at each particular step parameter that causes the biggest improvement in predictive accuracy is identified. Information value can also be utilised for inclusion of parameters. In this case, metric representing the difference among the distributions of high and low risks on that parameter is taken into account. Another method can be usage of a Chi-squared ($\chi 2$) test produced from a cross-tabulation of the attributes. However, this approach is accepted problematic from the view of multivariate statistics. Practical implementations might require utilisation of all approaches in the case of implementation (Hand and Henley, 1997: 528-529)

CHAPTER 3: RESEARCH DESIGN & METHODOLOGY

3.1 Research Philosophy

The term paradigm referring to philosophical thinking style is first conceptualised by (Kuhn, 1962). It is the researcher's perspective regarding the world which includes beliefs, way of thinking and principles. Those beliefs and assumptions form the view of aspect of the researcher regarding the world. Researcher anticipates, communicates and interacts with the world by means of his / her beliefs and principles. Hence, paradigm is like a glass for vision which assists researcher to assess methodological issues of a particular research problem in order to determine appropriate methods and the type of analyses to be used (Kivunja and Kuyini, 2017).

Positivist paradigm (positivism) is grounded in scientific research or science research and is dependent on rationalism. It adopts deterministic philosophy for anticipating influences and outcomes of the investigated phenomenon (Creswell, 2003, as cited in Mackenzie and Knipe, 2006). Positivist paradigm employs observation and measurement for understanding the surrounding. The way of interpreting and understanding the human behaviour should depend on experimentation and scientific method of investigation (Comte, 1856, as cited in Kivunja and Kuyini, 2017).

Interpretivist / constructivist paradigm is grounded on the interpretative understanding and depends on the idea that the "reality is socially constructed" (Mertens, 2005: 12). Researcher having constructivist / interpretivist paradigm depends on the views of the participants regarding the investigated phenomenon. Contrast to positivist paradigm, interpretivist does not often initiate the study with a theory. Instead, they use an inductive approach to explore meaningful patterns or establish a theory (Creswell, 2003, as cited in Mackenzie and Knipe, 2006).

Characteristics of the research employing positivist paradigm include implementation of empirical and analytical procedures, developing and testing hypotheses, quantification of findings, employing scientific method, ignorance of context and having the goal of developing a theory. Characteristics of research employing interpretivist paradigm, on the other hand, encompass depending on socially constructed beliefs, focusing on individuals and interdependencies among influences and causes, taking into account the context of the phenomenon and considering the interplay between the researcher and participants (Kivunja and Kuyini, 2017).

Quantitative studies rely on the positivist paradigm. Contrarily, qualitative studies depend on the interpretivist / constructivist paradigm. Hence, quantitative studies aim to measure and investigate influences and relationships between variables based on a framework (Denzin and Lincoln, 1994, as cited in Sale, Lohfeld and Brazil, 2002). Randomization, structured procedures, statistical methods and often questionnaires are applied. In qualitative studies, focus is on the process and meanings captured throughout this process. Techniques utilised, therefore, encompass interviews, focus group studies and participant observation (Sale et al., 2002).

Recent research problems have become more complicated and necessitated flexible research approaches. Mixed-method approach emerged from the combination of the recognized research paradigms with the aim of incorporating both quantitative and qualitative data (Mackenzie and Knipe, 2006). Sale et al. (2002) stated that arguments can better be anticipated when qualitative and quantitative approaches are incorporated in one single study, as a result of providing different perspectives. It is pointed out that mixed-method approach enables cross-validation (triangulation) by means of integrating different theories or data sources which facilitates to get a thorough understanding of the phenomenon (Denzin, 1970, as cited in Sale et al., 2002). Further, complementary nature of the two prevalent paradigms strengthens the research approach (Sale et al., 2002).

This dissertation, to a significant extent depends on positivist paradigm as it aims to explore and analyse causal relationships in a quantitative manner. Mainly, proposed models are tested with empirical data. However, models proposed in this study and its antecedents depend on the studies from associated literature in different contexts. It is, therefore important to explore new parameters and further patterns for the theoretical models within the proposed context. Hence, interpretivist approach is also adopted in order to discover contextual parameters related with the associated phenomenon.

3.1.1 Implemented Research Method

Regarding the research methodology of this dissertation mixed approaches are implemented. At the investigation stage, informal interviews are conducted with experts from finance sector. Relevant literature search provided a set of characteristics that are currently utilised in decision support for credit granting. System requirements captured through sectoral investigation, leaded to conduct a group project with academicians and practitioners from a wide range of disciplines including finance, management information systems, behavioural sciences and psychology. Group discussions and workshops leaded to decide potential list of parameters to be taken into account in the case of model construction. In order to justify importance of these variables and eliminate them based on a systematic basis focus group study is employed. This focus group study included two sessions with two different group of experts, which technically means two separate focus group studies.

As aforementioned for this dissertation, both qualitative and quantitative methods are utilised. For qualitative studies, it is crucial to determine the goal and scope of the study. Qualitative research's goal is to anticipate a specific social phenomenon by means of an examination process that provides getting deeper insight into the phenomenon in a gradual manner by analysing, examining and arranging the matter of the study (Creswell, 2003, as cited in Miah and Genemo, 2016: 6). Hence, qualitative research offers the opportunity of extensive information regarding the phenomenon. Regarding the design of the qualitative research, it is a process that includes developing research questions and procedures for accumulating, gathering, examining and reporting results (Creswell, 2007, as cited in Miah and Genemo, 2016: 7). In qualitative research, research questions are often open ended to provide examination of the problem for additional information, which facilitates to accumulate accurate research data (Guest et al., 2013, as cited in Miah and Genemo, 2016: 7). Qualitative research questions for discovering and determining main concepts, provided to gather prior knowledge and to make the topic clearer. This knowledge is than utilised to construct the quantitative study.

Accordingly, this dissertation employed mixed-method approach in the case of data collection. The advantage of mixed-method is that it provides performing triangulation. Triangulation enables gathering data by means of different methods with the aim of making data clear. This facilitates completeness and cohesion in the case of making inferences (Johnstone, 2004). In summary, triangulation enables utilizing different analysis techniques, exploring data from different theoretical aspects and analysing data with both quantitative and qualitative techniques (Ismail, 2011).

In this dissertation, focus group studies, semi-structured interviews are performed so as to analyse items from literature and explore new contextual information. Semi-structured interviews are conducted for supporting the focus group output. Moreover, a systematic review study is implemented for cross-checking the findings gathered. This led to construct a solid foundation for the quantitative study. Quantitative study was then applied to empirically test the proposed model.

3.2 Context of the Study

The goal of the literature review is to examine and reveal existing approaches utilised in credit risk assessment all over the world and to propose an appropriate credit scoring model for Turkey. It was, therefore important to gain deep insight into variables used in decision making process and to adopt them for the specific cultural context.

Practical contribution of this dissertation emerges from the developing country context for which the decision support system is proposed. At the investigation stage, existing decision –making processes for consumer loans in the relevant sector are examined and interviews are conducted with industry experts and main credit lending office. This lending office is the Credit Registration Bureau, which was established by 9 leading banks in Turkey. These interviews provided insight into existing credit evaluation processes and their shortcomings. Limitations of the existing decision support systems were as follows;

- None of the systems addresses the thin-file customers' credit access problem. These customers can either be young people that do not have credit history or low-income adults that do not have bank account or provable documents for traditional lending process.
- Credit scores for a significant number of potential applicants cannot be produced.
- Dominant systems in use for credit scoring depend on some widely adopted financial variables and potential benefit of some important data is neglected.
- Sectoral trends such as decision making with larger set of variables in the case of limited data are neglected.

- Potential supplementary tools such as psychometric assessment instruments do not have local origins and they do not fit social, economic and cultural background of Turkey.

It is, therefore necessary;

- To determine crucially relevant variables for decision making process which potentially enhances efficiency in credit granting.
- To propose a decision support system which employs psychometric tests.
- To propose a decision support system, which employs the classification algorithm which best addresses the decision problem.
- To develop a conceptual decision support system that can be tailored to similar contexts and credit lenders.

3.3 Research Procedure

Literature review conducted for this dissertation has depended on three step procedure including data collection, data analysis and combination of findings (Tranfield et al., 2003, as cited in Carè, Trotta and Cavallaro, 2013: 299). Major goal of literature review is to guide the researcher to examine the existing accumulation of knowledge and to designate a research gap that will additionally contribute to the body of knowledge (Tranfield et al., 2003, as cited in Carè et al., 2013: 300).

Within the qualitative research, inductive and deductive approaches are often utilised. Inductive analysis is found appropriate in the case of lack of studies associated with the phenomenon or in the case of studies that are disintegrated (Elo and Kyngas, 2008, as cited in Miah and Genemo, 2016: 7). This research applied inductive approach for classification and organization of the components of the phenomenon. Categories are discovered by means of analysis of articles on the field of debt and credit use domain. As a result, knowledge within the domain is demonstrated as concepts (categories) that reveal the examined fact.

Hence, first findings from the literature review assisted to gain insight into correlates of default. Parameters discovered from literature and their organization under categories led to establish the background of the focus group study. Semi-structured interviews and workshops for discussion with experts were performed for refining the findings. After the implementation of the focus group study, based on results a pilot study was designed and implemented.

In order to perform triangulation for establishing a solid quantitative research framework, findings from pilot study are supported with a qualitative content analysis. Hence, a systematic review involving the determinants of probability of default is performed for gaining a broad understanding. To the best of our knowledge, limited number of research has investigated the factors, that are influential on debt behaviour comprehensively and their evolution over time. This dissertation, dependent on findings from previous research and literature attempts to explore determinants, which are significant and to classify those variables into categories in order to provide a framework for the model construction. For this purpose, thematic classification referring to the technique of arranging variables that have been previously applied by the relevant literature (Samsu, Ismail and Sab, 2016: 60) was utilised. Analysis of results guided to develop the conceptual model for the credit scoring decision support system. To summarize, the research process and procedure conducted can be found in Figure 3.

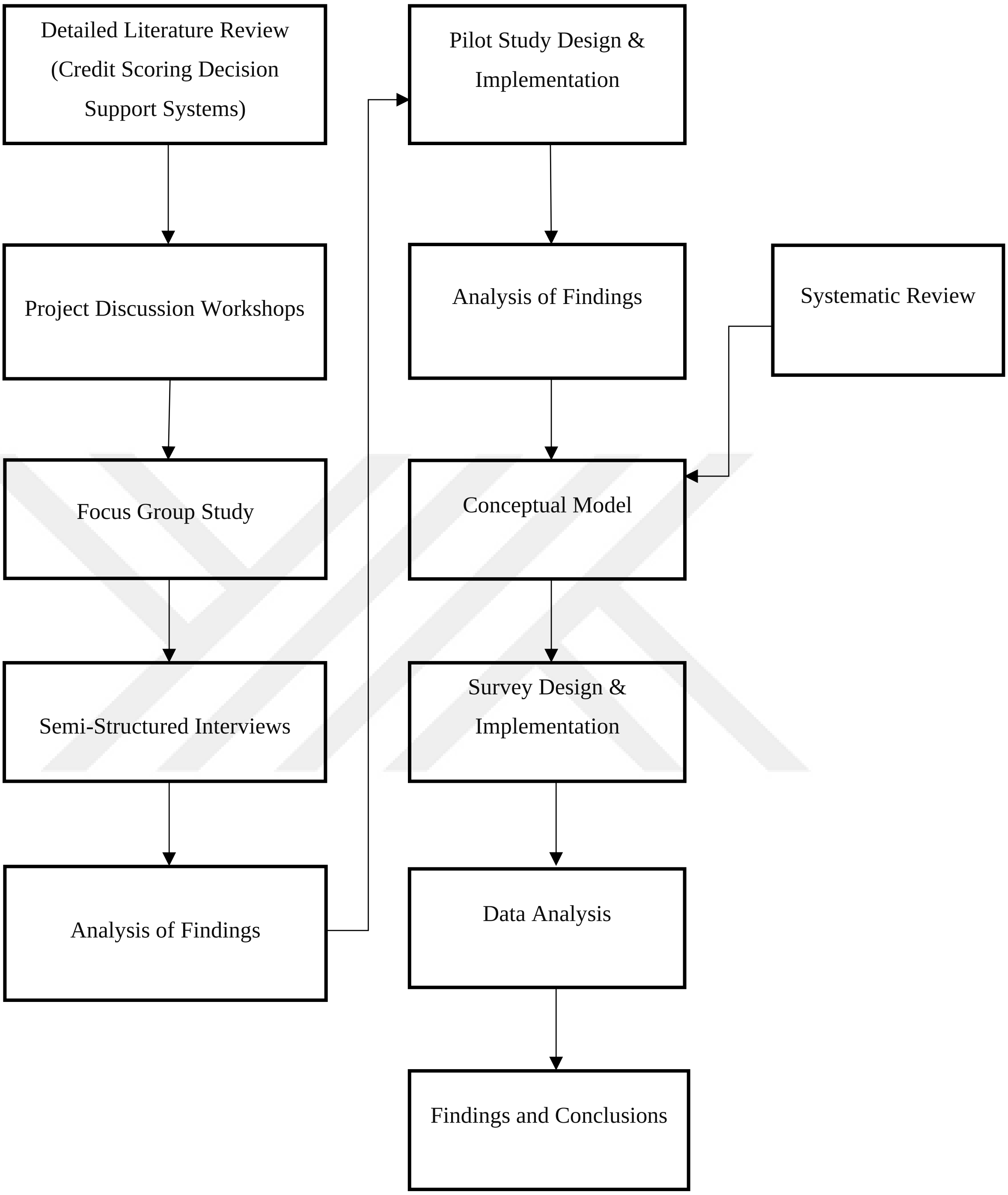

Figure 3: Research Procedure

3.4 Focus Group Study

Focus group method initially employed for commercial purposes at 1950s. Focus groups gather participants to discuss a particular topic with the aim of observing their reactions and exploring attitudes towards a topic. After, researchers got aware of the benefits of mixed-method approaches, focus group studies gained remarkable interest of social science researchers after late 1970s. Focus groups are conducted for complementary purposes and researchers often perform focus groups before the design of questionnaires (Bernard, 2000).

Bernard (2000) stated that a typical focus group study involves 6-12 participants, plus a moderator. Generally, 7 to 8 participants are involved in studies. Participation of more than 10-12 people is found difficult for the management of the discussion and the role of the moderator is important. Small sizes are good for deep discussions; however it can be easily dominated by some group members. Whatever the size of the group, skills and experience of the moderator are critical to overcome these issues. Another important issue is that familiarity and group members' knowing each other is unwanted for providing open discussions. Bernard (2000) also draw attention to homogeneity of the group members and the extent of homogeneity of the group should be adjusted based on the topic of the discussion and focus group's purpose. For eliminating ambiguity a codebook including definition of the variables is also suggested by (Creswell, 2013) for the implementation of focus group studies. Hence, this study followed these principles for focus group study design and implementation. The purpose of the focus group study and its procedure is explained below.

3.4.1 Focus Group Methodology

3.4.1.1 Purpose of the Focus Group Study

- Obtain new ideas, parameter suggestions, approaches and evaluations from the team of academicians, practitioners and industry experts
- Providing determination of the importance of these parameters in the credit risk assessment by sharing the literature findings
- Ensuring the classification of literature findings under particular main parameter groups
- Ensuring that the importance of newly suggested parameters are graded by other participants during the study

- Defining weights of the resulting main-parameter groups by Analytic Hierarchy Process (AHP)

3.4.1.2 Group Participants

1st Group: Six participants including industry practitioners in the fields of investment consultancy, banking finance, credit and risk management, and academicians studying behavioural finance.

2nd Group: Five participants including expert psychologists, HR experts, academicians studying in the field of marketing & consumer behaviour.

3.4.1.3. Setting of Discussions

Table 2
Setting of the Focus Group Study

Duration	Procedure
30 Minutes	<u>Opening Presentation</u> • Informing participants about objectives, topic, setting, duration, materials and protocol of the focus group study • Registration for participants' indication of their interest in voluntarily participating the focus group study • Share of focus group materials including post-discussion materials and registration forms • Share of focus group implementation procedure

Continuation of Table 2

120 Minutes	Discussion 1 (2 Parallel Sessions) For this session, participants are divided into two groups so as to conduct two parallel discussion sessions. One group forming of participants from financial background discussed indicators of creditworthiness from the aspect of finance. Another group of participants included expert psychologists, HR professionals and academics from associated field of study and they focused on the psychological aspects of the phenomenon. For facilitating in-depth discussions sessions of these two group of experts are conducted separately at first. • Clarification and discussion of the new criteria for psychometric and financial parameters was the major goal. For this purpose, this session is carried out in the form of brain-storming. • Participants are expected to reveal some parameters before the literature findings are shared. • The literature findings are not introduced to the researchers at first and the ideas of the participants are tried to be captured before revealing the literature findings. Each round started with a question, and completed at 15 minutes. Six questions in total are asked to participants. • After giving time to participants for answering each set of questions, discussions for the reasons of proposed parameters are performed. Participants are expected to give reasons for the parameters they recommended at this stage. • List of parameters proposed by the participants are taken, noted and recorded. • Questions and suggestions are taken, noted and recorded.

Continuation of Table 2

30 Minutes	<u>Assessment</u> As the major motive for the topic of this dissertation is initially originated from a project work, focus group study is conducted with project members who previously attended project group workshops. Assessment procedure between sessions is conducted by the project members so as to provide accurate analysis and to gather insights in moderating the focus group. This was helpful for eliminating variances in analysing focus group data. Hence; • Appreciation of the situation is made before the start of each discussion. The project group conducted a short workshop for evaluating the parameters captured through discussion one. • Proposed parameters in discussion one, are evaluated by the group to eliminate those signalling the same concepts. Terminology used by focus group participants was different. Thus, assessment aided eliminating variances and refining the set of parameters. • The set of parameters from discussion one is also compared with literature findings for further elimination and refining the parameter set. • A codebook, which was prepared in advance for explanation of parameters, and a document including refined parameter set are prepared for the next discussion. • Documents are prepared to enable severity of importance assessment through a 0 to 5 interval scale (0= Not at all important; 5: Extremely important) for each parameter. • Additionally, mapping of the parameters to broad categories (Main-Group Parameters) is aimed for the next session.
60 Minutes	<u>Discussion 2 (2 Parallel Sessions)</u> • Introduction of the literature finding to the participants • Representation of the focus group documents synthesized in the previous assessment workshop • Enabling severity of importance assessment of parameters • Enabling match of parameters with categories including financial / payment history factors, socioeconomic factors, demographic factors, personality factors, value, attitude and behaviour and situational factors
90 Minutes	<u>Assessment</u> • Researcher workshop for assessment of parameters and the definition of the ultimate categories in which they belong to • Preparation of findings for the next discussion

Continuation of Table 2

60 Minutes	<u>Discussion 3</u> • Combining the participant groups • Clarification of parameters and their categories, and their representation to participants • Providing information regarding the outputs of separate discussion groups • Informing members associated with the Analytic Hierarch Process (AHP) • Representation of AHP materials • Enabling the AHP procedure

3.4.1.4 Focus Group Structure

This section clarifies the focus group procedure by indicating questions, protocol and moderating issues related with the focus group structure.

- Registration forms including participants' names, job title and other demographic details are signed by the participants, and kept. Focus group discussion are recorded by means of digital voice recorders.

- In order to clarify or eliminate the sub-criteria of basic psychometric and financial parameters and to discuss new criterion proposals, participants are divided into two as financial group and behavioural group and two separate parallel sessions are held. Without having shared the literature findings, the participants are asked to reveal the parameters that could affect the prediction of individual credit risk by asking 6 questions. The questions can be found in Table 3.

Table 3
Focus Group Questions

Q1.	What are the characteristics of a reliable person in a debt relationship?
Q2.	What are the characteristics of someone who is not loyal to his / her debt?
Q3.	What should be considered in making loan granting decisions?
Q4.	What are the indicators of someone who demands a loan will not pay or disrupt his / her debt?
Q5.	What should be taken into account if someone with no prior credit history wants to get credit?
Q6.	Does the financial capability show that a person will pay his / her debt?

- Experts in each group have discussed the sub-criteria related to their field and stated the parameters that they think important. Participants are also asked to give reasons for the parameters they proposed at this stage and new ideas emerged in the sessions.
- After the session completed, the previous session is evaluated before the beginning of the other session and the findings of the literature are evaluated by taking the new parameters into account. Necessary documents are prepared in order to ensure that the new proposed parameters are included.
- The session continued in two different parallel sessions and the documents prepared are distributed to the participants. Participants in the financial group rated Financial, Socioeconomic, Demographic, Alternative, Situational, Personality, Value / Attitude and Behavioural factors, while participants in the Behavioural group rated Situational, Personality, Value / Attitude and Behavioural factors. The criteria in the documents (according to the significance level of 0-5) were evaluated. Participants were also asked to determine each parameter's main-group category.
- Before the final session, evaluation was performed and main-group parameters were determined according to the classification of the participants. At the beginning of the session, participants were informed about the final status of all parameters and the main-group parameters they categorized (Financial, Socioeconomic, Demographic, Alternative, Situational, Personality, Value / Attitude and Behaviour). In order to determine the significance of parameter groups, AHP method was applied and a comparison was made for the behavioural and financial groups. Then, the significance level of the six main-group parameters which were under the Behavioural and Financial Groups were compared. This group did not participate in the AHP evaluation as the significance level of the Alternative Factors was low in the rating. Table 4 represents maingroups for parameters.

Table 4
Factor Groups

Financial Parameter Groups	Behavioural Parameter Groups
Financial / Payment History Factors	Personality Factors
Socioeconomic Factors	Value, Attitude and Behaviour
Demographic Factors	Situational Factors

3.4.2 Findings from Focus Group Study

The most widely used method to analyse focus group data is the content analysis. Every attempt to analyse and anticipate focus group output demonstrates an analysis of content (Stewart et al., 2007, as cited in Hatten, 2014). Techniques associated with content analysis show variations depending on the goal of the analysis. Social constructivist analysis, other qualitative approaches, discourse analysis are considered within the content analysis approaches. Broadly, content analysis refers to the research methodology applying a number of systematic procedure on the data for making conclusions regarding the topic of study (Krippendorff, 2013, as cited in Hatten, 2014).

In most focus group studies, content analysis is utilised for deriving conclusions. However, there is still knowledge gap regarding the existence of a systematic methodology for content analysis in focus groups. This study adopted the methodology offered by Gothberg et al. (2013) for the analysis of group discussions. Each focus group sessions utilised alike protocols, they were audio recorded and they were transcribed. Each individual in the focus group study was considered as the unit of analysis. Their documents were separated, cleansed and made ready for analyses. Qualitative analysis focused on words, reasoning and the extent of dispute among participants. Procedures of Miles and Huberman (1994) was used for coding and application of thematic techniques. Qualitative analysis was applied to open ended questions one, two, three, four, five and six. Those findings were kept for the further interpretation of focus group data and they were combined with a statistical analysis of closed-ended questions' responses regarding the severity of importance of parameters. Thus, the transcripts and focus group material were analysed in detail by using a combination of qualitative and quantitative methods. Following tables demonstrate mean values for each parameter (ratings and responses were given on a five-point scale). Responses regarding the importance rating of these parameters were analysed by means of SPSS Software. Simple descriptive statistics were implemented to compute overall tendencies of group members (Table 5).

Table 5
Findings for Financial / Payment History Factors

Financial / Payment History Factors	Mean	Std. Deviation
Number of previously granted credits	4.40	0.894
Status of previous credit (Unpaid Credits or Ratio)	4.60	0.894
Insurance losses	2.40	1.140
Length of the relationship with bank	4.00	1.225
Number of bank accounts	3.60	1.140
Number of credit cards	4.00	0.707
Amount of liquid investments	4.00	0.000
Debt to income ratio	4.60	0.548
Credit card use patterns (Monthly payment rate)	4.40	0.894
Number of credit cards that exceeded the spending limit	4.20	0.837
Number of delinquent times (more than 90 days)	4.00	1.225
Days in arrears	3.80	1.095
Mobile and fixed line payment history	3.60	0.548
Presence of bankruptcy status declared in the previous year	5.00	0.000
Number of declined credit applications	4.20	0.447
New credit search	3.60	1.673
Type / diversity of credits used	3.60	1.949
Duration of credit history	4.20	1.304
Credit card debt / limit	4.00	1.732
Number of delinquent times (more than 30 days)	3.60	1.517

Among the financial / payment history factors most of them found important by the group participants. Members indicated that "presence of bankruptcy status declared in the previous year" is extremely important in assessment of creditworthiness. Participants also attained high level of importance to factors associated with credit history, credit card debt to limit ratio, status of previous credits, number of delinquent times, debt-to-income ratio, relationship with bank, number of credit cards, credit card use patterns and length of credit history. Attainment of high level of importance to most of the financial predictors confirms the literature findings associated with the credit scoring decision support models mostly incorporating financial data. Together with financial predictors, socioeconomic factors have been widely used for building probability of default models. Some common indicators of socioeconomic status detected in the relevant literature presented to focus group participants for importance rating. Table 6 represents the findings regarding the socioeconomic predictors rated by focus group participants.

Table 6
Findings for Socioeconomic Factors

Socioeconomic Factors	Mean	Std. Deviation
Monthly expenditures total (More than income)	3.80	1.304
Income	4.00	1.225
Disposable personal income	4.00	1.225
Income of spouse	3.40	0.894
Occupation	3.80	1.304
Health insurance ownership (Private)	3.40	.894
Length of the current employment	3.40	1.140
Unemployment pattern in the previous year	3.80	1.643
Home ownership status	3.60	0.894
Number of dependents	3.40	1.140
Consistency of the residential status (10 years)	2.60	1.817
Number of vehicles owned	2.40	0.894
Estimated value of vehicles owned	2.40	1.140
Number of properties owned	3.00	1.414
Estimated value of properties owned	3.40	0.894
Number of employees (If owner of a company)	3.00	1.225
Company net value	3.60	0.894
Length of the company ownership	3.00	1.581
Education	3.00	1.581
Education of spouse	2.00	1.225

Overall picture depicts that, members did not assign very high level of importance to socioeconomic indicators compared to financial predictors. Income and disposable personal income were found more important than the other predictors. However, most factors were found at least moderately important by the group members. Demographical factors were often traditionally integrated to credit risk models. However, a significant amount of research investigated demographic factors from the aspect of life cycle hypothesis of savings. Thus, income, consumption and expenditure patterns changing by life cycle stages of individuals were examined and proposed by the relevant literature. Hence, a set of demographic factors were presented to focus group for assessment of their applicability within the studied context and for evaluation of their severity of importance. Table 7 represents findings for demographic factors.

Table 7
Findings for Demographic Factors

Demographic Factors	Mean	Std. Deviation
Gender	3.00	1.225
Age	3.60	1.140
Marital status	3.00	1.225
Family life cycle stage	3.80	1.304

Highest degree of importance was attained to family life cycle stage of individuals in assessing creditworthiness. In parallel with this criterion, age was also considered as an important indicator by the members. Importance level of gender and marital status were found moderate by the participants. Traditional credit risk assessment considers character as an important facet. However, it is not considered and integrated into credit risk models. Merely, theoretical studies have focused on the subject so far. Practical cases emerged with the trend of psychometric assessments. But the implementations are still in their infancy. Hence, personality traits mentioned in those theoretical and practical work were gathered and a set of personality traits were represented for focus group discussions (Table 8).

Table 8
Findings for Personality Factors

Personality Factors	**Mean**	**Std. Deviation**
Conscientiousness	4.70	0.483
Agreeableness	3.78	1.093
Emotional stability / Neuroticism	3.60	1.506
Openness to experience	2.90	1.524
Extroversion	3.00	0.667
Sensation seeking	3.50	1.581

Conscientiousness was found as the strongest predictors of default behaviour by the participants. Hence, they attained relatively high level of importance to this parameter. All other personality traits were found at least moderately important in assessment of creditworthiness. Factors grouped as value, attitude and behaviour factors mainly depend on the theoretical studies focusing on influence of attitude, subjective norms and perceived control on intention. Consequently, intention affects the behaviour of individuals (Ajzen, 1991). Accordingly, the set of predictors in Table 9 from associated literature were presented to focus group participants.

Table 9
Findings for Value, Attitude and Behaviour Factors

Value, Attitude and Behaviour Factors	Mean	Std. Deviation
Compulsive buying	4.20	1.135
Social comparisons	3.44	1.130
Risk aversion	4.67	0.500
Collectivist culture	3.60	1.265
Attitudes towards money (Power & Prestige)	4.00	1.054
Attitudes towards money (Retention)	4.50	0.707
Time horizon	4.70	0.483
Decision making style (Rational)	4.50	0.707
Decision making style (Intuitive)	4.30	0.823
Locus of control	4.33	1.323
Financial literacy	4.60	0.699
Social sanctions	4.70	0.675

Compared to other group of parameters the extent of importance attained to this set of predictors were higher in general. Except from social comparisons and collectivist culture, all parameters were found very important by the participants. One facet of creditworthiness have concentrated on social factors and events effecting psychological condition of individuals. Stressors effecting people's lives were often associated with delinquent behaviour. Hence, a wide range of potential sources of stress or negative events may be associated by the default behaviour of borrowers. These situational factors and causes of strain were identified in Table 10.

Table 10
Findings for Situational Factors

Situational Factors	Mean	Std. Deviation
Spouse or child's death	3.56	1.424
Change in residence	2.30	1.059
Unexpected medical expenses	4.10	1.101
Divorce / marital separation	4.00	1.054
Imprisonment	4.40	0.966
Death of the close family member	2.60	1.265
Personal injury	3.90	0.994
Marriage	3.00	1.247
Loss of job (dismissal)	4.22	1.302
Retirement	3.00	1.247
Unexpected changes of health status of a family member	3.40	1.174
Participation of a new member to the family	2.80	1.033
Reorganization at the workplace	2.88	1.126
Death of a close friend	0.80	0.789

Source: Holmes and Rahe (1967)

Among the list of negative life events (Holmes and Rahe, 1967), not all of them were found very important. Importance given to marital separation, medical expenses, imprisonment and loss of job were higher than the other negative life events. These stressful events were considered more important in the case of assessing creditworthiness. Personal injury, death of spouse / child, unexpected changes in the health and marriage were also considered at least moderately important events that could be linked with the default behaviour. Literature findings signal evolution of parameters used for credit risk assessment as a result of changing trends. Data from alternative sources have been heavily investigated and incorporated into risk models currently. This set of factors, actually refer to sources of data that signal the aforementioned socioeconomic, financial, personality and attitudinal indicators of creditworthiness. Hence, some indicators derived from literature can be found in Table 11.

Table 11
Findings for Alternative Factors

Alternative Factors	**Mean**	**Std. Deviation**
Social Media / Posts and Tweets	2.40	0.894
Facebook likes	2.00	1.414
Online profile / LinkedIn	2.20	1.483
Social network number of friends / consistency of number	1.20	0.837
Twitter user name	1.00	1.225
Other user names	1.20	1.095
Installed applications	1.20	1.304
Mobile phone usage patterns (uses in the day / differentiation in morning evening)	1.20	1.095
Frequency of mobile phone use	1.00	0.707
Mobility	2.40	1.517
E-commerce history	2.40	1.140

Overall picture depicts that, alternative factors gained less level of importance compared to other set of predictors. Depending on the fact that, this set of parameters include data sources that enable information regarding behaviour, personality and socioeconomic status, they are utilised for practical purposes in the case of supporting quick decision making when there is limited data about the borrower. Hence, one reason behind low scores for alternative predictors may be that participants assigned weights without considering data scarcity and practical applications.

In addition to those factors, focus group participants offered parameters that can be associated with debt repayment behaviour or probability of default. These parameters were obtained through the qualitative analysis of open-ended responses and discussion transcripts. Sixty-two significant themes (codes) emerged and these parameters offered by the participants were presented to the other group members for rating the significance of each new parameter. Results were analysed by SPSS Package by means of applying basic descriptive statistics. Offered parameter set is presented in Table 12.

Table 12
Findings for New Parameters

Parameters Offered by Focus Group Participants	
Reference information*	Social security payments (as an employer or employee)
Level of debt*	Inconsistent behaviour in decision making (Instability)*
Additional income*	Behaviour in psychometric tests (Quick decision making)*
Previous payments / number of defaults*	Cash flow projection*
Life standards	Length of the passport ownership
Change in social status (Wanting to Maintain the Former Living Situation Although the Economic Situation is Worsening)*	Use of TV packages (Social status indicator)
Purpose of credit (Using credits out of purpose)*	Insurance diversity
Openness*	Household information
Persuasive skill (Why credit is requested?)	Debt to income ratio*
Area of residence	Ethical considerations (repayment)*
Trading on the stock exchange*	Psychopathy type*
Ethics and Islamic finance principles	Non-resistance to authority
Close family bonds	Image management
Low price sensitivity (easy acceptance of terms & conditions)*	Honesty-humility (lying tendency)
Irrational exuberance (whether or not to check conditions)*	Stress tolerance
Age & gender combination (Men taking less risk as they get older)	Shyness
Impulsivity	Bad habits
Automatic payment orders *	Analytical thinking
Giving contradictory information to different institutions*	Ambitiousness
The difference between the amount demanded and amount offered by bank (loan amount)*	Optimism
Intention not to repay*	Imaginative
Conjuncture sensitivity of income*	Fearlessness
Membership of civil society organizations	Location of birth
Entitlement information on equity (Land Registration)	Lack of self-control
Call center history (with bank)	Gender of children
Messy and missing documents	Risk tolerance assessment*
Rejected credit applications*	Ethical principles (Family)
Location (Application from a very different place from residential area)	Egocentrism
Psychological problems in the last month	Perceptions regarding the cost of fail to comply repayment terms*
Self-praise	Experience of legal sanctions
Others' attitudes towards debt	

* Indicates that significance level of the parameter was scored 4 or over 4 by the participants.

Various parameters were emerged in this analysis. Together with other set of predictors, these variables were kept for further evaluation with regard to inclusion in the final model.

3.4.2.1 Deriving Weights with AHP Implementation

In some cases, financial knowledge is scarce as the applicants are not able to show proof of evidence for their financial history. For these cases, psychometric information can be incorporated for complementing data on hand. Building statistical models depends on large datasets. In the case of psychometric data, lack of enough data makes the statistical processes inapplicable. However, priorities for group of parameters such as financial and non-financial data can be reflected in the constructed model by means of multicriteria evaluation. Hence, in order to incorporate different facets of creditworthiness into credit risk model, Analytic Hierarchy Process (AHP) of Saaty (1980) was used. This method has been employed in many decision problems from a wide range of field (Saaty, 2012). This study aims to integrate psychometric data and to incorporate a psychometric module in a decisional system so as to be used as a complementary or secondary screening tool.

Initially, establishment of a database including psychometric information is difficult due to lack of this kind of data. Hence, application of statistical methods may not produce accurate results. Depending on these facts, a judgemental approach is valuable for complementing and integrating experiences and ideas of experts into decision making models (Baklouti and Baccar, 2013). Aouam et al. (2009) also proposed a two-stage model incorporating statistical and judgemental approaches for the purpose of credit scoring. C. Serrano-Cinca et al. (2016) used AHP for indicating preferences of experts. Similar to work of those, this dissertation used AHP for determining preferences of experts and this information was kept for comparison and combination with statistical results.

Not all the group of parameters would have the same importance. Hence, last session of the focus group study was allocated for AHP implementation process in order to determine intensity of importance of main-group parameters. AHP, which provides importance of elements with respects to each other was conducted to determine relative weights for the group of parameters. AHP is a decision making model that breaks down a complicated decision problem into a hierarchy. Procedure of AHP involves four steps including construction of the model, giving priorities, evolution and synthesizing of the results (Saaty, 1980). For the first step, criteria and alternatives were determined for pairwise comparisons. The second step conducted pairwise comparisons. The group of experts in the focus group were asked "At what extent criterion X is important relative to criterion Y?" After getting a comparison matrix, relative weights were calculated by means of the comparison matrix. Judgements consistency were provided by the consistency ratio (C. Serrano-Cinca et al., 2016).

Previously prepared documents with AHP format were presented to participants and they were informed about the process. Depending on the fact that set of alternative variables were found comparatively less significant by the members, this group was not included for the further process. Ultimate version of the main-group parameters and classification results were also presented to participants. Numerical scale presented for comparison can be found in Table 13.

Table 13
Pairwise Comparison Scale

Scale for Pairwise Comparisons		
Intensity of Importance	**Definition**	**Explanation**
9	Extreme importance	Being extremely favourable towards one element pairwise comparisons
8		
7	Very strong importance	Being very strongly favourable towards one element pairwise comparisons
6		
5	Strong importance	Being strongly favourable towards one element pairwise comparisons
4		
3	Moderate importance	Being slightly favourable towards one element in pairwise comparisons
2		
1	Equal importance	Represents equal contribution

Source: Saaty (2012)

Pairwise comparison matrix that enabled assessment of participants assisted the decision making of the participants for priorities. Cells of the comparison matrix represent numerical scale so as to reflect members' judgement regarding the importance of one element over another. Comparison matrix that was presented to focus group member is represented in Table 14.

Table 14
Comparison Matrix

Overall Comparison																		
Financial Factors	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Psychometric Factors**
Financial Group of Parameters																		
Financial / Payment History Factors	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Socioeconomic Factors**
Financial / Payment History Factors	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Demographic Factors**
Socioeconomic Factors	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Demographic Factors**
Psychometric Group of Parameters																		
Personality Factors	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Value, Attitude and Behaviour Factors**
Personality Factors	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Situational Factors**
Value, Attitude and Behaviour Factors	**9**	**8**	**7**	**6**	**5**	**4**	**3**	**2**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**Situational Factors**

Depending on each participant's judgement, overall weights for the aforementioned criteria were calculated by means of an AHP software package implementing methods. Approximation of the overall weights are presented in Table 15.

Table 15
AHP Results for Predictor Groups

	Weight	**Main-Group Parameters**	**Weight within Group**	**Overall Weight**
Financial Factors	70.90%	Financial / Payment History Factors	60.50%	42.89%
		Socioeconomic Factors	31.20%	22.12%
		Demographic Factors	8.30%	5.88%
Psychometric Factors	29.10%	Personality Factors	34.70%	10.10%
		Value, Attitude and Behaviour Factors	27.30%	7.94%
		Situational Factors	38.00%	11.06%

AHP provided consensus among focus group members. Financial module of the decision support systems integrating financial / payment history factors, socioeconomic factors and demographic factors was found more important than psychometric factors similar to findings of the previous literature. Members indicated that this set of parameters (70.90%) were more important than psychometric parameters (29.10%). Among financial parameters, financial / payment history factors (60.50%) were weighted more heavily than the socioeconomic (31.20%) and demographic (8.30%) factors. Within the psychometric group intensity of importance assigned to personality (34.79%), value, attitude and behaviour factors (27.30%) and situational factors (38.00%) was relatively close to each other. Finally, with respect to overall weights, focus group participants strongly prioritized financial / payment history factors (42.89%) over the other set of parameters. This was followed by socioeconomic factors (22.12%). It is interesting when psychometric factors were considered together, they accounted for (29.10%) of the overall weights. Findings represented that experts prefer financial information to psychometric information. However, psychometric parameters were remarkably important for participants and findings of this assessment was kept for further investigation and model construction phase.

3.5 Pilot Study

Previously, in order to construct the theoretical foundation of the decision support system, literature findings were combined and analysed. Parameters that were found significantly associated with the repayment behaviour and probability of default were discussed in a focus group study. This focus group study applied mix methods so as to refine findings from the literature. In the focus group study, the importance of the parameters was evaluated by the participants and the participants offered new parameters in addition to parameters gathered from the relevant literature. Categorization of the parameters was provided by the expert group and after that AHP implementation was performed. At the end of this process, the importance levels and weights of the parameter groups were determined.

Some of the predictors mentioned by focus group members indicated similar concepts and had the same meanings although the terminology was different. Hence, semi-structured interviews were conducted with experts for eliminating the parameter set again and mapping the similar concepts indicating the same phenomenon. Some group of variables especially, remarkable number of psychometric predictors gained high scores as a result of importance rating of focus group participants. Thus, in order to eliminate those variables and to construct a solid foundation a pilot study was designed and implemented. This section explains the procedure of the pilot study which was designed for the psychometric predictors and applied to a sample of individuals who had debt repayment problems or experienced default in the past and individuals who had good repayment behaviour or did not experienced problematic debt situation.

3.5.1 Semi-Structured Interviews

The interviewers provided detailed explanations regarding the aim of the study. Respondents were presented overall findings of the focus group study regarding the psychometric predictors. These predictors included personality, value, attitude and behaviour factors, and situational factors that forms the psychometric aspect of the proposed system. Hence, the predictors and their definitions were presented to interviewees with results of the focus group study (Table 16).

Table 16
Definition of Predictors

Predictor	Definition
Conscientiousness	It refers to people's work discipline, importance and attention put into jobs that have been faced in life. Being careful, organized, planned, disciplined, prepared, stable, committed to ethical principles, focusing on success, having ability of finishing a job started and thinking throughout are associated with conscientiousness (Costa and McCrae, 1992).
Agreeableness	It refers to altruistic, modest, polite, faithful, thoughtful, friendly, conciliatory, sympathetic and friendly individuals (Office of the Director of National Intelligence, 2011).
Emotional stability / Neuroticism	It is a tendency to experience negative emotions. It refers to pessimistic, jealous, nervous, cowardly, anxious, insecure, hypersensitive and unstable individuals (Costa and McCrae, 1992).
Openness to experience	It is about the individual's imagination, foresight, adaptation to change and flexibility. It refers to individuals who are intellectual, creative, sophisticated, curious, imaginative and open to new ideas (Costa and McCrae, 1992).
Extroversion	It is about individual's self-confidence in interacting the environment. It refers to social, ambitious, energetic, talkative, fun-loving, expressive, friendly and socially confident individuals (Zainol et al., 2016).
Sensation seeking	It is one of the personality traits defined by the ability to, take physical, social, legal and financial risks for experiencing new and complex feelings and emotions (Harlow and Brown, 1990).
Compulsive buying	It is a disorder that emerges, as a result of the person's inability to control this motive of feeling strong impulse to buy which may leave the person in a financially difficult situation (Ridgway et al., 2008).

Continuation of Table 16

Social comparisons	It shows the perceptions of how a person evaluates himself / herself in various contexts compared to others. It refers to individuals' determination of their own social and personal values based on their comparison with others. This can be on issues such as success, intelligence, charm or health (Corcoran et al., 2011).
Risk aversion	The tendency to take risks under unknown circumstances without knowing what the results would be. Individuals with high level of risk aversion are able to tolerate high level of risks, whereas low level of risk aversion indicates avoidance from risks (Ding et al., 2009).
Collectivist culture	This type of culture is dominated by social values and norms rather than personal goals. Belonging to a community and goals of the community are considered more important. Being pushed out of society for any reason is perceived as a great punishment. Therefore, individuals with a high collectivist culture level consider the thoughts and judgments of others about themselves and act in accordance with the norms of the society (C. C. Chen, Chen and Meindl, 1998; Hofstede and Bond, 1984)
Attitudes towards money (Power & Prestige)	Money is seen as an ultimate symbol of success and a tool for influencing people. According to such individuals who consider money as a symbol of power and prestige, money means to gain status and power by means of possessions such as cars, houses, and clothes etc. (Yamauchi and Templer, 1982).
Attitudes towards money (Retention)	It refers to expressing an extra cautious attitudes towards spending money and feeling strong bad senses regarding the loss of money in the case of spending (Yamauchi and Templer, 1982).
Time horizon	It refers to planning horizon with individuals. The long-term focus means that the individual has a virtuous, persevering, determined and thrifty attitude for future rewards while short-term focus indicates that instant gratification is preferred for a future awards (Kim and DeVaney, 2001).
Decision making style (Rational)	It is a form of decision making based on rational evaluation of details and all alternatives. In the case of decision making gathering information about options, examining alternatives and considering consequences of the decisions were taken into account (Scott and Bruce, 1995).
Decision making style (Intuitive)	It is the form of decision making based on intuitions rather than data. Decisions are made without thinking about the options and their possible consequences enough. This king of individuals are usually abrupt, reactive and hasty in the case of decision making (Scott and Bruce, 1995).
Locus of control	It refers to personality structure of the individuals who hold the external elements responsible from their failures and negative events that they encounter. This type of individuals think that their life is out of their control and mostly depends on luck, fate and others (Rotter, 1966).
Financial literacy	Ability to use financial knowledge and competences for effective management of financial resources (Gerardi et al., 2013).
Social sanctions	It refers to the belief of individuals that they will be sanctioned and punished when they do not obey the rules (Besley and Coate, 1995).
Situational factors	Situational factors include the negative life events such as the death of family members or relatives, personal disability, illness, divorce / separation, retirement, dismissal and unexpected medical expense that affect the lives of people and cause strain (Holmes and Rahe, 1967).

Interview guide followed in this study is adopted from the established procedure of Ismail (2011) and followed the recommendations of Rowley (2012) and Turner III (2010). The questions were formed dependent on the goal and scope of the study. Interviewees' opinions with regard to the findings of literature and focus group study were tried to be explored for gaining deep insight and refining the conceptual model. Interviews were performed in an informal setting and overviews were provided regarding the aim and procedure of the interview. All interviewees were academicians in associated fields of study. Profile of the interviewees are given in Table 17.

Table 17
Detail of Interviews

Interviewee	Field of Study	Gender	Duration
I1	Finance	Male	30 minutes
I2	Behavioural Sciences	Female	30 minutes
I3	Behavioural Sciences	Female	30 minutes
I4	Behavioural Sciences	Female	30 minutes
I5	Behavioural Sciences	Female	30 minutes
I6	Psychology	Female	30 minutes

Based on the recommendation of Rowley (2012) approximately 30 minutes were allocated for each interview. Questions asked to interviewees were delivered in the established order as follows.

Table 18
Interview Questions

Q1.	Do you agree that these constructs and predictors are important in evaluating creditworthiness of individuals?
Q2.	Do you agree the severity of importance of these predictors that were allocated by experts?
Q3.	Do you have any changes and additions for the list of predictors?
Q4.	Do you have any changes for the conceptual model constructed based on literature and focus group findings?

The main purpose of the interviews was to establish the ultimate conceptual model for psychometrics. Hence, eliminating irrelevances and detecting additional information for the modification of the model was the major goal. Based on the data-coding procedures of Miles and Huberman (1994), list of variables, gathered from the literature review and presented at the focus group study are guided to the data analysis process, and every variable was coded. The interviewees' responses regarding the existing list of variables did not contradict. Entire participants agreed with the importance of the variables. At another step, focus group findings and the ratings for the level of importance were presented to the participants. Sensation seeking was proposed for elimination by the participants. Sensation seeking was reported as a facet of Big Five personality type, and together with collectivist culture focus group study allocated relatively low level importance to those variables. Interviewees did not contradict with the focus group and attained low level of importance to these variables. Interviewees agreed with the complexity of some concepts and indicated that Big Five personality measure was sophisticated enough to encompass certain facets of personality. Hence, in order to prevent redundancy of personality indicators Big Five personality inventory was suggested by the participants for inclusion in the final model. However, regarding the importance of these five dimensions there were mixed comments about their relevance with the outcome that the study aims to assess.

Regarding the value, attitude and behavioural factors, interviewees screened out the variables and findings of the focus group study. Social comparisons which was also found relatively less important was suggested for exclusion by the interviewees. Among situational factors, contrast to focus group participants, interviewees gave higher priority to the event of “death of a close family member” and suggested for inclusion among situational factors. Major issue highlighted by the interviewees was that adverse life events had a cumulative effect in causing strain in people’s lives and consideration of diverse events with regard to their influence of repayment is important. Events that were found contextually inappropriate were proposed for exclusion. As a result, situational factors incorporated nine life events. Predictors from literature findings and from qualitative studies were guided to construct the questionnaire.

However, there were some mixed findings associated with some issues, which were highlighted by interviewees. These comments and arguments were noted for providing evidence in the case of anticipating pilot study results. Some participants indicated that the concept of “collectivist culture” was probably misunderstood, as its meaning presented to focus group participants more emphasized social motivation and subjective norms. It was reported that norms in collectivist cultures were more influential in attitudes and behaviour of individuals. Regarding the “compulsive buying”, some interviewees indicated that compulsive buying was a consequence of a self-control problem, and making inappropriate and purposeless decisions were closely related with lack of self-control. Related to this argument, some focus group participants suggested that lack of self-control might affect probability of default or over-indebtedness. Another argument was on the Big Five inventory. Some participants indicated that openness to experience as it was discovered less important in the focus group study might be excluded from the conceptual model. Although focus group participants rated the agreeableness characteristic as important, interviewees criticised that and suggested for exclusion. Based on the comments of some interviewees, conceptual relationship of risk preferences (risk aversion) and time preferences were noted for the construction of the conceptual model.

3.5.2 Setting of the Pilot Study

Sample of the pilot study was 61 individuals in total. 26 of the respondents indicated that they were experienced default status. Defaulters were identified based on questions comprising their past repayment behaviour and current level of debt. 35 of the respondents were in good credit status, which represents responsible debt repayment behaviour and at most a moderate level of debt. Regarding the sampling, convenience sampling among non-probabilistic sampling techniques was employed. Convenience sampling is a kind of non-random sampling focusing on easily accessible, geographically convenient, available and willing individuals of the target population for practical purposes (Dörnyei, 2007). It is preferred for easy access and affordability in the case of data collection. Convenience sampling basically assumes that the target population is homogeneous and can lead to misguidance for formal inductive conclusions regarding the population. However, some characteristics of the sample can be detected and evaluated (Etikan, Musa and Alkassim, 2016). In addition, purposive sampling was also used in the case of accessing individuals having repayment problems. Purposive sampling referring to judgemental sampling technique as well, aims to select participants on purpose depending on a set of participant characteristics. The researcher determines what to explore and seeks for participants who are able to and willing to give information on the studied phenomenon (Bernard, 2002).

3.5.2.1 Dependent Variables

Debt status is a categorical variable and defined as the dependent variable for the pilot study. In the case of selecting the independent variables, findings of the focus group study was taken into account. Five questions were included in order to explore financial behaviour and past constraints of participants. 1) DBT1=Have you ever delayed the payment of your debt (credit card or loan repayment)? 2) DBT2= Have you ever paid interest for not repaying your debt? 3) DBT3= Have you ever delayed your payment of your debt more than 90 days? 4) DBT4= Have you ever gone on trial or experienced execution for your debt? 5) DBT5= Have you ever experienced foreclosure for not repaying your debt? If the individual experienced at least two of these events, he / she was considered to have bad credit (DEBT variable= 1). Otherwise, the individual was considered to have good credit (DEBT variable= 0).

If the participant indicated that he / she had experienced only first two events; additional screening was provided with the following variables: 1) DEBTLVL= What is your current debt amount compared to your income? 2) DBTcrd= What is the amount of your current credit card debt compared to your income? 3) DBTbnk= What is the amount of your current credit debt amount compared to your income? 4) DBTff= What is the amount of your current debt to your family / friends compared to your income? 5) DBTothers= What is the amount of your current debt to landlords / utility suppliers compared to your income? The options to reply these question were: none; less than half of my monthly income; equal to half of my monthly income; equal to my monthly income; equal to twice of my monthly income; equal to four times of my monthly income; more than four times of my monthly income. The strategy used to categorize debtor and non-debtors was as follows:

1. If the participant did not give affirmative responses at least two of DBT1, DBT2, DBT3 and DBT4, DBT5 questions, responses to debt level questions (DBTcrd, DBTbnk, DBTff and DBTothers) were considered. If participants reported “debt amount equal to or more than twice their monthly income” for entire questions, they were considered as bad credit (DEBT variable= 1).

2. If the participant gave affirmative responses only for the first two of DBT1, DBT2, DBT3 and DBT4 and DBT5 questions, responses to debt level questions (DBTcrd, DBTbnk, DBTff and DBTothers) were considered. If participants reported “debt amount equal to or more than twice their monthly income” for at least three questions, they were considered as bad credit (DEBT variable= 1).

3.5.2.2 Independent Variables

Based on Social Readjustment Scale of Holmes and Rahe (1967), a list of life altering events that could explain the individuals' risky behaviour were determined. Those events were refined and the list of events were adjusted based on qualitative studies. Participants were questioned whether they had financial strain associated with life events they experienced. Hence, the corresponding question which was included was as follows: 1) Which one of the following events have you experienced at least once? The options were: LFEVT1= Divorce / marital separation; LFEVT2= Marriage; LFEVT3= Spouse or child's death; LFEVT4= Loss of job (dismissal); LFEVT5= Death of the close family member; LFEVT6= Personal injury; LFEVT7= Unexpected changes of health status of a family member; LFEVT8= Unexpected medical expenses; LFEVT9= Imprisonment; LFEVT10= Others. In this case, 10 dummy variables were created. Positive responses for the experience of these events was coded (=1).

In order to determine financial literacy levels of participants, they were questioned based on 10 multiple choice questions regarding the financial knowledge and its depth. The questions were adopted from previously utilised financial literacy surveys (S. Agnew and Harrison, 2015; Kennedy, 2013; van Rooji, Lusardi and Alessie, 2007). Participants' scores were determined as the percentage of right responses to ten questions. Missing answers were treated as wrong. Other psychological and attitudinal variables are presented in Table 19.

Table 19
Psychological Variables and Sources

Construct	**Variable Code**	**Sources**
Risk Aversion	RA	(Sharma, 2010)
Time Horizon	TH	(Bearden, Money and Nevins, 2006)
Decision making Style	DMR	(Scott and Bruce, 1995)
	DMINT	
Compulsive Buying	CB	(Ridgway, Kukar-Kinney and Monroe, 2008)
Money Attitudes (Power & Prestige, Retention)	POWPRS	(Baker and Hagedorn, 2008; Yamauchi and Templer, 1982)
	RTN	

Continuation of Table 19

BIG FIVE	CONSCIENTIOUSNESS	(Alkan, 2007; Gümüş, 2009)
	AGREEABLENESS	
	OPENNESS to EXPERIENCE	
	EXTRAVERSION	
	NEUROTICISM	
Locus of Control	LCEXT	(Rotter, 1966)
	LCINT	
Social Sanctions	SOCS	(Bhatt and Tang, 2002; Griffin and Husted, 2015)

Depending on the fact that main purpose of the study was to investigate psychological variables, some commonly used demographic (gender, marital status, age) and socioeconomic (monthly income, household income, education and occupation) information were requested from participants.

Items were scored based on a 5-point Likert scale (1= strongly disagree; 5= strongly agree). In order to implement scales in different context, adaptation and implementation process requires a set of procedures including translation and retranslation. For this process, procedures proposed by Brislin (1970) was adopted. English form of the materials were written in a clear and understandable form without using long sentences. Translators were knowledgeable on the topic and content to be translated. First materials were translated from their original language (English) to Turkish, and then another translator blindly translated back them to English. Three different raters evaluated the original and back-translated forms in order to discover mistakes causing different meanings. When mistakes were explored, translation and back-translation steps were repeated with altering the original version if it was necessary. After, no meaningful errors were detected, translated content were tested on Turkish speaking people. According to pre-test findings and observations, materials were revised and reformed. Finally, both versions were employed on bilingual subjects and their responses were compared.

3.5.3 Analysis of Pilot Study Data

The Exploratory Factor Analysis (EFA) gives insight into the number of necessary factors so as to properly symbolize the data by statistically obtaining the factors. EFA reveals factors structures and proves evidence for the items of the constructs (Hair et al., 2014).

For the pilot study data, EFA was applied to extract factors by means of applying method of principal components with Varimax rotation. Factors having Eigen-values greater than one were extracted (Hair et al., 2014) and factors meeting the Kaiser-Meyer-Olkin (KMO) criterion were included. KMO is a measure of sampling adequacy and indicates applicability of factor analysis. Values between 0.5 and 1 indicate eligibility for factor analysis, whereas values lower than 0.5 signify that factor analysis is not appropriate for the data. In addition, communalities referring to total variance that a variable shares with the other variables are important and can be derived from factor loadings (Altunışık et al., 2012). Accordingly, communalities greater than 0.5 are accepted (Hair et al., 2014). In terms of factor loadings, Hair et al. (2014) stated that factor loadings over 0.5 are practically significant. Hence, items having factor load less than 0.5 and items that were loading on more than one factor were excluded.

EFA revealed the following outcomes: for risk aversion, EFA demonstrated that risk aversion items apparently loaded on one factor. Likewise, items of time horizon and compulsive buying loaded on one factor as well. Items of decision making style, attitudes towards money and locus of control loaded on two factors. Regarding the social sanctions, analysis revealed a four-factor solution. In the case of Big Five scale, factor structures could not be obtained properly. Factor scores were estimated and bivariate correlations among dependent variable and independent variables were evaluated.

Before conducting analysis for bivariate correlations between independent variables and dependent variable, tests of normality were conducted. At most cases findings demonstrated that the data significantly strayed from normal distribution. Accordingly, nonparametric tests and measures of rank correlation, specifically (Spearman's rank correlation coefficient) was employed. Regarding the correlations of dependent variable with risk aversion, time horizon and compulsive buying, Spearman's Rho (r_s) values of 0.375, 0.363 and -0.377 indicated a weak correlation between the relevant variable and the independent variable ($p< 0.01$). Retention dimension of attitudes toward money was also had weak positive relationship with the dependent variable ($r_s=0.358$, $p< 0.01$). For the two factors of social sanctions F3 and F4 Spearman's Rho (r_s) values of 0.308 and 0.379 again demonstrated weak positive relationship ($p< 0.01$). Consequently, Table 20 summarizes whether the bivariate correlations produced significant results or not for each independent variable.

Table 20
Findings for Bivariate Correlations

Financial Literacy	Insignificant
Risk Aversion	Significant
Time Horizon	Significant
Decision making Style	Insignificant
Compulsive Buying	Significant
Money Attitudes (Power & Prestige)	Insignificant
Money Attitudes (Retention)	Significant
Big Five	NA
Locus of Control	Insignificant
Social Sanctions F1	Insignificant
Social Sanctions F2	Insignificant
Social Sanctions F3	Significant
Social Sanctions F4	Significant

Regarding the situational variables, correlation of the number of life events with the dependent variable was investigated. There were significant differences among groups in terms of experience of adverse life events (($\chi^2(3) = 13{,}273^a$, $p < 0.01$). This pilot study did not reveal enough proof to analyse the relationship between some independent variables and the dependent variable. This might be because of the relatively small sample size or the scales utilised for this study. For instance, in the case of decision making style construct, it was observed that most questions were not clearly anticipated by the respondents and contradictory answers were detected. The similar problems occurred in terms of Big Five scale as well. Factor analysis results were problematic and only items for conscientiousness and extraversion were extracted meaningfully. Because of the mixed results, more support from literature was required. For this purpose, literature was reviewed in a systematic manner in order to provide more support for the construction of the conceptual model. The following section explains the systematic review process and its findings.

3.6 Systematic Review

Performing literature review in a systematic manner, enhances the value of the review process and the findings are achieved by means of a transparent process (Carè et al., 2013: 300). The aim of this review was to explore the correlates of probability of default. First, literature was examined to explore broad aspects of the phenomenon. Relevant criteria were determined and a qualitative content analysis was employed to produce themes inductively to combine with the components of the system model. Findings of the content analysis determined the set of factors for designing the conceptual model of the proposed Decision Support System. To summarize, the procedure applied for this stage can be seen in Figure 1.

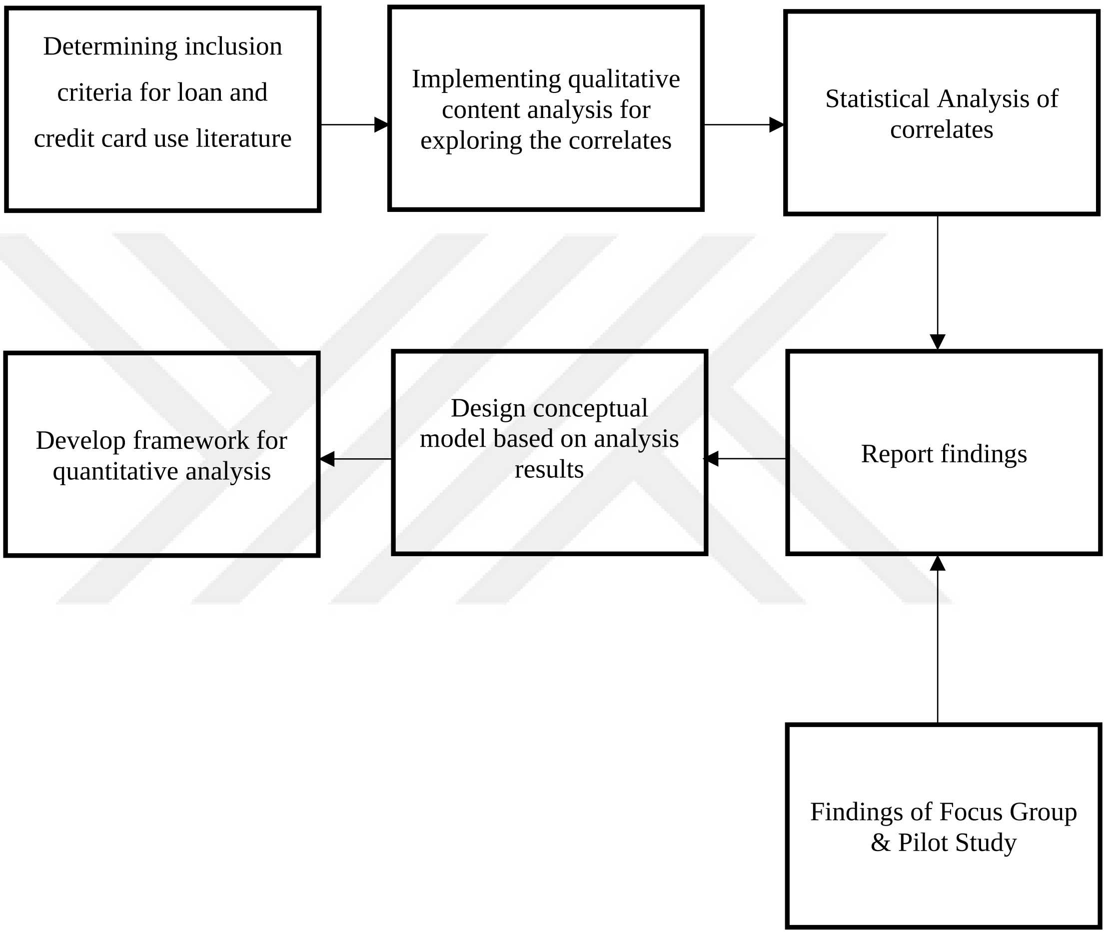

Figure 4: Procedure for the Construction of the Conceptual Model

The analysis concentrated on exploring correlates of probability of default and/or problematic debt, which can be utilised for credit risk assessment. For the analyses process, which was employed to papers within this domain inclusion criteria were determined. Elo and Kyngas (2008) stated that within the content analysis no principles of behaviour exist for data analysis and they proposed "preparing, organising and reporting" as analysis stages (Elo and Kyngas, 2008, as cited in Miah and Genemo, 2016: 8). The initial concern at the stage of preparation was to determine the scope of the research and areas that were relevant to research problem. Using the keywords "probability of default", "problematic debt", "outstanding debt", "delinquency", "credit scoring", "credit risk assessment", "repayment behaviour", "decision support systems for credit risk assessment" relevant databases were investigated. Extensive research effort was put on in order to handle the phenomenon from a broad aspect. Unit of the analysis was determined as the journal articles that involved topics mentioned above.

Criteria for the selection of units of analysis were defined as follows: 1) Including articles having publication dates from 1985 to 2019, 2) Excluding non-academic papers, 3) Excluding articles having lower sample sizes (based on analysis applied), 4) Including studies with quantitative findings, 5) Excluding studies do not indicating dependent & independent variables explicitly, 6) Including studies with sufficient statistical findings, 7) Excluding studies except from in English language, 8) Excluding books, dissertations and conference papers. Preparation stage guided to discover 705 articles from eight databases such as Science Direct, Elsevier, Springer, ERIC, SAGE etc. After detection and elimination of duplicates, 549 studies were left. Inclusion and exclusion were applied to dataset and 108 articles were provided for content analysis. Document analysis requires looking through cursorily, reading with complete investigation and anticipation (Bowen, 2009, as cited in Miah and Genemo, 2016: 9). Hence, all units of analysis were examined to understand the contents in order to derive important categories (Figure 5).

Organising and reporting stages of inductive content analysis include open coding and development of the meaningful categories and/or concepts. Open coding process involves reading throughout, and remarking and highlighting critical issues (Elo and Kyngas, 2008, as cited in Miah and Genemo, 2016: 10). Depending on notes taken, comments and content underlined data was coded. Additional reading provided to revise and adopt the coded data in order to make assure adequacy of acquired data from articles.

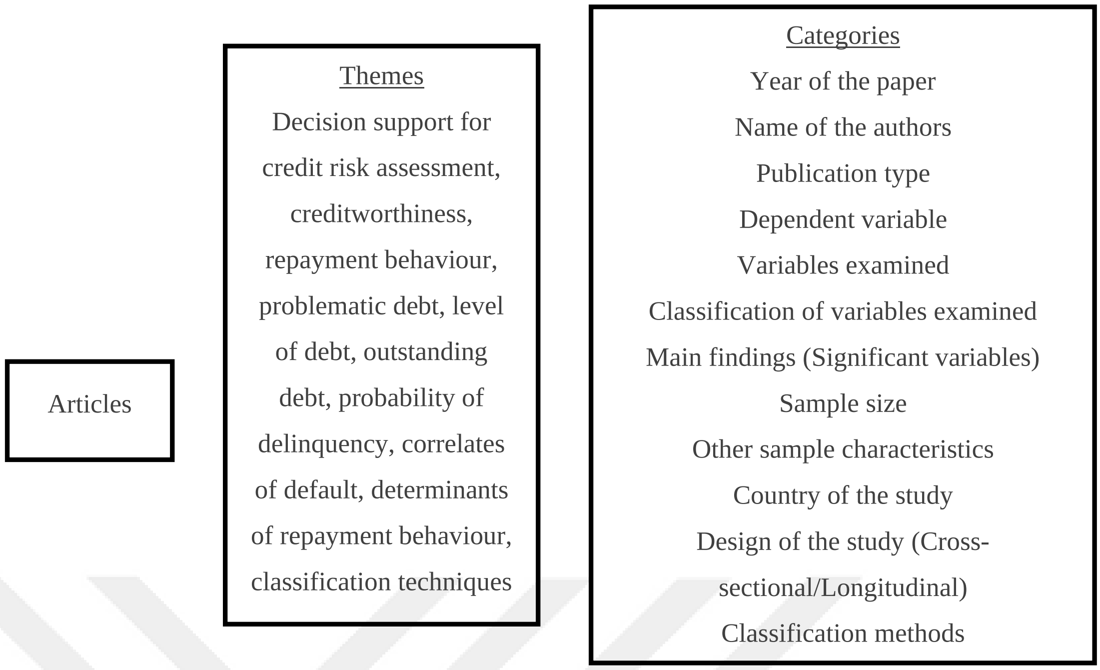

Figure 5: Themes and Categories

3.6.1. Findings of the Systematic Review

Associated with the credit risk assessment, reviewed papers approached the phenomenon from different aspects. Therefore, diverse depended variables were detected. Under the dependent variable category four main types of outcome domain were revealed: Probability of default (32), probability of over-indebtedness (problem debt) (46), financial behaviour (responsibility) (26) and credit misuse (11). Some studies examined more than one dependent variable, hence the total number may not add to the total number of articles examined (108).

A wide range of predictor (independent) variables were detected from the systematic review. Results were synthesized based on the number of articles, which considered that specific independent variable, their distribution based on four dependent variables, number and percentage of effects which were reported statistically significant in articles. For the categorization of independent variables the same framework revealed and employed at early stages of research (literature review & focus group & semi-structured interviews) was utilised. Additionally, some different characteristics related with macroeconomic indicators, health of individuals and characteristic related with educational loan repayment were detected. These variables were assessed under "Others" category. Table 21 demonstrates the group categories for independent variables.

Table 21
Classification of Predictor Variables

Socioeconomic	Value, Attitude and Behaviour
Demographic	Situational
Institutional / Financial	Alternative
Personality	Others

3.6.1.2 Distribution of Articles based on Predictor Variables

Detailed research on credit risk assessment revealed a comprehensive list of factors. Meaningfully synthesizing previous research results, guided to gain insight into overall picture regarding the statistical findings of the credit risk assessment models. Socioeconomic and demographic factors were the most widely used variables in the reviewed studies (67%). Value, attitude and behavioural factors were examined in 57% of the articles, while 45% of the studies focused on financial factors. Other remarkable number of studies (35%) examined personality characteristics.

3.6.1.3 Personality Variables

Self-control and emotional stability were significant determinants of the dependent variable in whole studies they were taken into account. 67% of the articles reported significant statistics for self-efficacy, 60% for openness to experience, 71% for impulsiveness, 67% for self-esteem, 75% for optimism, 83% for extraversion, 64% for conscientiousness, 60% for agreeableness, and 50% for neuroticism. Self-efficacy, openness to experience, conscientiousness and agreeableness had effect on financial behaviour (responsibility), probability of debt and over-indebtedness, whereas emotional stability / neuroticism and optimism were reported as significant determinants of financial behaviour and over-indebtedness.

3.6.1.4 Value, Attitude and Behavioural Variables

Social motivation / attitudes towards debt (others), attitudes towards loan repayment, consumer behaviour / expenditure pattern, perceived financial well-being, economic socialisation and religious practices were constantly explored as significant determinants in entire studies they were examined. 69% of studies indicated significant effects for financial literacy, 75% for risk aversion, 80% for delay of gratification, 83% for attitudes towards money, 80% for compulsive buying, 85% for attitudes towards credit use, 87% for financial management and 64% for locus of control. A few studies reported significant effects of variables comprising social comparisons, perceived importance of credit terms and conditions, awareness of loan repayment, general ethical principles, particular credit attitudes (use for some specific purposes) and ways of coping with stress.

3.6.1.5 Situational Variables

Unexpected life events and their influence on default and over-indebtedness have been widely examined. Consistently with the focus group findings and pilot study, remarkable number of studies (90%), explored within the scope of the systematic review, indicated that situational variables had significant effect on outcome domain. Among those studies, 60% discovered significant effect on probability of default.

3.6.1.6 Socioeconomic Variables

Socioeconomic variables examined and revealed significant effect on the dependent variables comprised of income, employment status, family income, household type, number of children, family income, length of employment, number of dependents, occupational class, household size, education, wealth and social class. Wealth was a significant predictor of outcome variable in all studies it was included. Number of dependents were displayed the same pattern. Additionally, employment status, social class and family income were found significant influencers of the dependent variable in more than 70% of the total articles.

3.6.1.7 Demographic Variables

Similar to previous findings of focus group, semi-structured interviews and literature review revealed that family life cycle, age, marital status and gender were commonly assessed and implemented demographic variables. Ethnicity was also widely examined and 72% of the articles reported significant results for ethnicity. Family life cycle stage was an important predictor as 100% of the studies considered this variable revealed its significant effect. More than half of the studies reported significant findings for age and marital status. It was also a considerable finding that family life cycle stage was consistently influencer of probability of default in all studies it was considered.

3.6.1.8 Financial / Payment History Variables

A wide list of factors derived from systematic literature review for financial variables. Some of them were consistent with the previous findings such as length of the relationship with bank, debt to income ratio, type / diversity of credits used. Additionally, although terminology was different, variables that were detected from focus group and systematic review process were derived from each other such as number of debts, financial assets, liquid investments, credit card use patterns, number of credit cards that exceeded the spending limit, number of delinquent times, number of declined credit applications, number of previously granted credits, behind schedule payments, credit limit or credit card debt to limit ratio. Entire articles within the scope of this review reported significant influence of length of the relationship with bank, debt to income ratio, type / diversity of credits used and behind schedule payments on the outcome domain. 90% of the studies reported that number of credit cards was a significant indicator, while 88% of articles indicated that past credit behaviour was significantly determined probability of default. Account balance was also an important indicator as 67% of articles reported significant effect. A few studies (less than three) reported significant effect for minimum required payment (for credit cards) to income ratio, other sources of debt, guarantees, debt to assets ratio and perceived advantage of reporting bankruptcy on probability of default.

3.6.1.9 Alternative Variables

As indicated before these indicators are detected from various resources and gathered from social media, online websites, e-commerce platforms and telecommunication providers. Digital data is mostly used for complementing the available but limited data for deriving personal and behavioural characteristics. Sociodemographic profiling of individuals can be obtained by means of these alternative data sources. Within the scope of the systematic review, historical occurrence of these group of variables was also examined. Socioeconomic and demographic variables were mostly in use for risk assessment in the early periods. Interest of researchers on the psychological and situational predictors were heavily observed between 1991 and 1996. After, 1990s integration of different perspectives into credit risk assessment was noticed. Financial variables were also dominant and more than half of the articles focused on financial indicators till the end of 2008, and after that there was a moderate decrease in the utilisation of financial variables but still considerable amount of papers examined financial indicators. The same pattern was observed for demographic and socioeconomic variables as well. Contrarily, after 2015 there was a considerable increase in number of papers emphasizing alternative indicators. Among entire articles published after 2015, 35% of them investigated the effect of alternative data on credit risk assessment. The explored predictors included SMS usage patterns, number of friends in social network platforms, qualification of the network, posts, retweet activity, geographical location, number of followers, mobile phone calls (duration, timing etc.) and an extensive set of indicators produced from various data points. Rapid increase in utilisation of alternative predictors can be attributed to the initiatives for psychometric profiling of individuals for practical purposes.

3.6.1.10 Other Variables

Some studies approached the credit risk assessment from macro level aspect by examining macroeconomic factors. Relatively less amount of studies considered macroeconomic factors such as unemployment rate, gross domestic product (GDP), interest rate and census tract's income. Other group of variables focused on health related characteristics of individuals and investigated their effect on probability of default or over-indebtedness. For instance, overall stress and risky drinking behaviour were mentioned as determinants of default behaviour. Some studies reported effect of body mass, perceived health status, depressive symptoms, physical activity and nutrition behaviour on the over-indebtedness. However, these variables were included and proved statistical evidence for a few studies. Moreover, they were outcomes of some particular psychological characteristics. For instance, drinking and gambling behaviour may stem from impulsiveness and self-control problems. Hence, those variables were not evaluated with regard to inclusion in the conceptual model.

CHAPTER 4: RESEARCH MODEL & HYPOTHESES

This chapter explains the research model and hypotheses to be tested. The chapter begin with the brief explanation of constructs. As most of the constructs are discussed in detail in previous sections, the rationale behind considering the construct for the model development is emphasized. Socioeconomic, demographic, financial, personality, behavioural and situational variables proposed for the conceptual model are presented and hypotheses are discussed.

4.1 Independent Variables

4.1.1 Personality Variables

Personality variables included in the pilot study were revised based on findings and systematic review. Some variables detected in the systematic review was previously evaluated in the qualitative studies. Therefore, they were not considered for the conceptual model, as a result of the consensus. For instance, respondents agreed that characteristics such as self-esteem, self-efficacy and optimism were various facets of characteristics defined by Big Five. However, openness to experience and agreeableness were not found very important determinants of debt repayment and default behaviour by experts. Systematic review study's results supported this idea, as except from agreeableness and openness to experience facets of Big Five, other facets revealed evidence for significant effect in many studies. Hence, the following factors were considered for the conceptual model to be tested: ***Self-control*****:** Systematic review study revealed that self-control was a significant determinant of probability of default, over-indebtedness or negative financial behaviour in entire studies it was examined, for instance (Nurcan and Bicakova, 2010; Strömbäck et al., 2017; L. Wang, Lu, et al., 2011; Webley and Nyhus, 1998). Taking into qualitative findings into account, inappropriate financial decisions, impulsiveness and compulsive buying were probable consequences of self-control problems. Importantly, compulsive buying was found associated with indebtedness, whereas decision making style did not produce sound results in the pilot study. Strong evidence for the influence of self-control revealed in the systematic review, and consequences of qualitative studies guided to consider self-control for the conceptual model of the study instead of compulsive buying and decision making style.

Conscientiousness: Among facets of Big Five inventory, focus group participants attained higher level of importance to conscientiousness. Systematic review study also revealed that remarkable amount of studies proved evidence for the effect of the conscientiousness (Bernerth et al., 2012; Donnelly et al., 2012; Ganzach and Amar, 2017). Additional support was provided by Davey and George (2011), Kubilay and Bayrakdaroglu (2016) and Yang and Lester (2014). ***Emotional Stability (Neuroticism):*** Emotional stability / instability or neuroticism facet of Big Five was found a strong determinant of financial behaviour and problematic debt (Davey and George, 2011; Kubilay and Bayrakdaroglu, 2016). Studies of Donnelly et al. (2012), Ganzach and Amar (2017), and Zainol et al. (2016) supported the argument as well. Brougham et al. (2011), Nyhus and Webley (2001), and Pirog and Roberts (2007) used the term emotional stability / instability for examining the same phenomenon and found significant evidence regarding its influence. Consistently, focus group participants gave priority to emotional stability and extraversion more than the facet of openness to experience. ***Extraversion:*** Reviewing the articles systematically indicated that more than 80% of the studies within the scope of the review reported significant findings regarding the influence of extraversion on default or repayment behaviour (Davey and George, 2011; Harrison and Chudry, 2011; Kubilay and Bayrakdaroglu, 2016; Yang and Lester, 2014). Additional support was found by Brown and Taylor (2014), Donnelly et al. (2012) and Zainol et al., (2016). Consequently, hypotheses of the study were specified as follows:

H1a: Self-control has significant impact on debt behaviour

H1b: Conscientiousness has significant impact on debt behaviour

H1c: Emotional stability has significant impact on debt behaviour

H1d: Extraversion has significant impact on debt behaviour

4.1.2 Value, Attitude and Behavioural Variables

Depending on the qualitative findings and pilot study, risk aversion, attitudes towards money, time horizon, compulsive buying and social sanctions were considered for the conceptual model at first. First findings of these studies were screened out and results were fairly consistent with the systematic review findings. When systematic review findings were screened out more than 70% of studies reported significant effect of impulsiveness, delay for gratification and compulsive buying. As aforementioned before, qualitative findings highlighted self-control problems as root cause of impulsivity and compulsiveness. Hence, instead of these characteristics self-control was included in the conceptual model. Reviewing literature systematically, social motivation / attitudes towards debt (others), attitudes towards loan repayment, consumer behaviour / expenditure pattern and economic socialisation were constantly explored as significant determinants in entire studies they were examined. 85% of studies reported significant results for attitudes towards credit use and 87% for financial management.

Risk Aversion: Risk aversion or risk tolerance referring to risk preferences of individuals evaluates willingness to take risks and tendency of engagement in risky behaviours. Being risk averse is important when it comes to financial decisions (Borghans et al., 2008). Tokunaga (1993) explored that risk taking was associated with credit associated problems. Brown et al. (2013) discovered that attitudes towards risk and risk aversion were significant influencers of problematic debt. Sidoti and Devasagayam (2010) found positive correlation between attitudes towards risk and credit misuse. Borghans et al. (2008) also indicated that risk preferences and time preferences were conceptually linked with each other. Additionally, depending on the criticism of interviewees supporting this idea, "risk aversion" remained for detailed investigation. ***Attitudes towards Money:*** Yamauchi and Templer's (1982) study was one of the most important study revealing psychological perspectives of money. Tokunaga (1993) found significant results for "power & prestige" and "retention" dimensions of money attitudes. Bhardwaj and Bhattacharjee (2010) also indicated that probability of default was significantly influenced by "power & prestige" dimension of money attitudes. Palan et al. (2011) revealed proof of evidence for effect on credit misuse. L. Wang, Lu, et al. (2011) explored significant results for both "retention" and "power & prestige" dimensions. Additionally, qualitative findings revealed high level of importance for these factors. Pilot study explored significant effect for the "retention". Although "power & prestige" dimension did not prove strong link with the dependent variable in the pilot study, strong support from systematic review and strong agreement of qualitative study participants provided to retain this factor for further investigation. Accordingly, "power & prestige" and "retention" dimensions were remained for further analysis. ***Financial Management Behaviour:*** Previously, time orientation was found as a significant indicator of repayment behaviour, supporting the literature that individuals with long-term orientation are more responsible in managing their financials. In contrast, short-term oriented individuals have tendency to do give immediate decisions and prefer immediate gratification (Sharma, 2010). Financial management behaviour domain captures the intended behaviour to be measured by the time orientation and decision making styles. Accordingly, more than 85% of studies reported that financial management was a significant determinant of repayment behaviour. Hence, in order to introduce a more comprehensive and focused construct instead of time orientation and decision making style, financial management behaviour was included in the proposed conceptual model. ***Social Sanctions:*** Social sanctions refer to the belief of individuals that they will be sanctioned and punished when they do not obey the rules. In developing nations, existence of interdependencies among individuals is important and various enforcement mechanisms in these cultures are influential in affecting individuals' behaviour. The extent of sanctions which one may be imposed and how it is anticipated by the borrower is an important influencer of behaviour (Besley and Coate, 1995). Qualitative findings also supported that cost of default and its social penalties are perceived more seriously in collectivist cultures. Hence, in order to investigate individuals' perceptions regarding their explosion to social penalties, "social sanctions" construct was included. ***Social Motivation (Subjective Norms):*** Subjective norms are described as the perceived social pressure over individuals with regard to involving in a particular behaviour (Ajzen, 2008, as cited in Kennedy, 2013: 14). Subjective norms are described as the perceived social pressure over individuals with regard to involving in a particular behaviour (Ajzen, 2008, as cited in Kennedy, 2013: 14). According to Theory of Planned Behaviour (Ajzen, 1991), subjective norm is one of the main components in anticipating human behaviour. Based on the theory, if one have positive attitudes towards debt repayment and have support from others (family, friends etc.), and if he / she has repayment capability as well, then it is expected that repayment behaviour will take place (Ismail, 2011). Qualitative findings suggested the use of "social motivation" instead of "collectivist culture" as the phenomenon intended to be tested was found conceptually associated with "social motivation". Systematic review study demonstrated that social motivation / attitudes towards debt (others) were explored as significant influencers of repayment in entire studies they were examined. For instance, S. E. G. Lea et al. (1995), Limbu (2017) and J. Wang and Xiao (2009) found important findings regarding the effect of social motivation. ***Spending Behaviour:*** "Number of credit cards that exceeded the spending limit" was given high priority according to qualitative findings. Further investigation and systematic review revealed that consumer behaviour / expenditure pattern (S. Costa, 2012; Norvilitis et al., 2006), bad shopping habits (Nurcan and Bicakova, 2010) were found important correlates for debt repayment. Entire research within the scope of the systematic review proved evidence regarding the effect of these factors. Factors such as payment pattern (behind schedule payments), spending behaviour (Baek and Hong, 2004), economic behaviour (Livingstone and Lunt, 1992), level of shopping (Rutherford and Devaney, 2009), credit card expenditure (L. Wang et al., 2014) include factors proposed so far by the relevant research. ***Risky Credit Behaviour:*** "Credit card use patterns (Monthly payment rate)", were given high level of importance by focus group participants. In the context of loan repayment and problematic debt, previous research have suggested several conceptually related factors such as existing credits' repayment status (Jiang, Wang, Wang and Ding, 2018), perceptions and awareness of loan repayment (Ismail, 2011), time preference (delayed payment) (Webley and Nyhus, 1998), credit card debt to income ratio (Domowitz and Sartain, 1999), payment pattern (Baek and Hong, 2004), projected debt repayment (Norvilitis et al., 2006), problematic credit card use (Norvilitis and MacLean, 2010), use of credit card (Šušteršič et al., 2009), attitudes towards debt (L. Wang, Lu, et al., 2011) and credit card responsible use (Vieira et al., 2016). Synthesizing the research above, the following hypotheses were developed. Ultimate items to be included in the main survey are demonstrated in Table 22.

H2a: Risk aversion has significant impact on debt behaviour

H2b: Attitudes towards money (power & prestige) has significant impact on debt behaviour

H2c: Attitudes towards money (retention) has significant impact on debt behaviour

H2d: Financial management behaviour has significant impact on debt behaviour

H2e: Social sanctions have significant impact on debt behaviour

H2f: Social motivation has significant impact on debt behaviour

H2g: Spending behaviour has significant impact on debt behaviour

H2h: Risky credit behaviour has significant impact on debt behaviour

Table 22
Constructs and Items Included in the Main Survey

Constructs	Code	Items	Source
Risk Aversion	RA1 RA2 RA3 RA4 RA5 RA6	"I tend to avoid talking to strangers" "I prefer a routine way of life to an unpredictable one full of change" "I would not describe myself as a risk-taker" "I do not like taking too many chances to avoid making a mistake" "I am very cautious about how I spend my money" "I am seldom the first person to try anything new"	(Sharma, 2010)
Self-control	SC1 SC2 SC3 SC4 SC5	"I have a hard time breaking bad habits" "I do things that feel good in the moment but regret later on" "I am good at resisting temptation" "I often act without thinking through all the alternatives" "I get distracted easily"	(Strömbäck et al., 2017)
Attitudes towards money (Power & Prestige)	PP1 PP2 PP3 PP4 PP5 PP6	"I use money to influence people to do things for me" "I admit I purchase things to impress others" "I own nice things in order to impress others" "I behave as if money is the ultimate symbol of success" "Sometimes boast about how much money I have" "I spend money to make myself better"	(Baker and Hagedorn, 2008; Yamauchi an Templer, 1982)
Attitudes towards money (Retention)	RT1 RT2 RT3 RT4	"I do financial planning for the future" "I put money aside on a regular basis for the future" "I save now to prepare for my old age" "I follow a careful financial budget"	(Baker and Hagedorn, 2008; Yamauchi an Templer, 1982)
Spending behaviour	SB1 SB2 SB3 SB4 SB5 SB6 SB7	"If I have money at the end of the month, I have to spend it" "I buy without thinking its consequences" "I often buy things even though I could not afford them" "I often buy things to make myself better" "I feel restless on days when I do not get to shop" "I only make minimum payments on my credit card" "I often do not have enough funds to pay my credit card bills"	(Nga, Yong and Sellappan, 2011)

Credit card usage & payments (Risky credit behaviour)	RC1 RC2 RC3 RC4 RC5 RC6 RC7	"My credit cards are usually at their maximum limit" "I frequently use the available credit on one credit card to make payments on the other credit card" "I often make minimum payment on my credit card bills" "I am delinquent at making payments on credit cards" "I take cash advances on my credit card" "I frequently have to use bank credit to make payment on my credit card bills" "I frequently have to borrow others to make payment on my credit card bills"	(Nga et al., 2011; J. A. Roberts and Jones, 2001)
Financial management behaviour	FM1 FM2 FM3 FM4 FM5 FM6 FM7 FM8 FM9	"Paid all my bills on my bills on time" "Kept a written or electronic record of my monthly expenses" "Stayed within my budget or spending plan" "Maxed out the limit on one or more credit cards" "Made only minimum payments on a loan" "Began or maintained an emergency savings fund" "Saved for a long-term goal (buying car, education, home etc.)" "Comparison shopped when purchasing a product or service" "Contributed money for retirement account, bonds, stocks or mutual funds"	(Dew and Xiao, 2011)
Social motivation (Subjective norms)	SM1 SM2 SM3	"Most people who are important to me think I should be responsible in using credit or borrowing money" "My friends and family think I should be responsible in using credit or borrowing money" "I want to do what my family and friends think I should do regarding credit and borrowing money"	(Limbu, 2017)
Social sanctions	SOC1 SOC2 SOC3	"I would feel embarrassed for not repaying my debt if members of my community know about it" "I would feel embarrassed for going on trial (for of not repaying) if members of my community know about it" "I would feel embarrassed for exposing foreclosures (for not repaying) if members of my community know about it"	(Bhatt and Tang, 2002; Griffin and Husted, 2015)

Continuation of Table 22

	SOC4	"I would feel afraid of being excluded from community for not repaying my debt"	
	SOC5	"I would feel afraid of being excluded from community for going on trial"	
	SOC6	"I would feel afraid of being excluded from community for exposing foreclosures"	
	SOC7	"I would feel afraid of losing my reputation in the community for not repaying my debt"	
	SOC8	"I would feel afraid of losing my reputation in the community for going on trial"	
	SOC9	"I would feel afraid of going on trial for not repaying my debt"	
	SOC10	"I would feel afraid to be jailed for not repaying"	
	SOC11	"I would feel afraid of having calls from creditors for not repaying"	
Big Five (Conscientiousness, Neuroticism, Extraversion)	CS1	"I put effort to do any work completely"	(Alkan, 2007; Gümüş, 2009)
	CS2	"I am carelessness"	
	CS3	"I am a trustworthy person to be responsible from a task (work, homework, job)"	
	CS4	"I tend to be messy"	
	CS5	"I tend to be lazy"	
	CS6	"I work resolutely until I'm done with a job"	
	CS7	"I work efficiently"	
	CS8	"I plan and apply these plans"	
	CS9	"I can easily get distracted"	
	NR1	"I'm a pessimist, sad person"	
	NR2	"I feel comfortable, I do not get stressed"	
	NR3	"I am a nervous person"	
	NR4	"I am an anxious person"	
	NR5	"I am emotionally stable, do not get unhappy easily"	
	NR6	"My mental state quickly changes"	
	NR7	"In tense situations and environments, I can stay calm"	
	NR8	"I can easily get angry"	
	EX1	"I am a talkative person"	
	EX2	"I am an introvert person"	
	EX3	"I am an energetic person"	
	EX4	"I motivate other people"	
	EX5	"I have self-confidence"	
	EX6	"I am an outgoing, social person"	
	EX7	"Sometimes I am shy"	
	EX8	"I am a silent person"	

4.1.3 Situational Variables

Literature findings supported the significant influence of adverse life events on repayment problems and probability of default (Chakravarty and Rhee, 1999; S. Costa, 2012; Fay et al., 2002; Godwin, 1999; Rogers et al., 2015; Stone and Maury, 2006). Considerable amount of research within the scope of the systematic review (60%) discovered significant effect for situational factors on probability of default. Pilot study confirmed the results as well. Furthermore, experiencing adverse life events were found significantly associated with repayment problems in the pilot study. Life events that were previously adjusted based on qualitative findings, revised again as a result of responses of participants. Under the "others" category, participants emphasized some situations such as "house relocation", "bankruptcy of the business" and "employment problems of spouse". Hence, the list of life events were reconsidered so as to encompass the options of "moving house", "bankruptcy of the business" and "employment problems of spouse". Based on these findings, associated questions were refined and developed as follows:

Which one of the following events did you experience at least once? (In the period of financial constraint or prior to experiencing financial constraint). The options were: LFEVT1= Divorce / marital separation; LFEVT2= Marriage; LFEVT3= Spouse or child's death; LFEVT4=Death of the close family member; LFEVT5= Personal injury (for yourself); LFEVT6= Unexpected changes of health status of a family member; LFEVT7= Loss of job (dismissal); LFEVT8= Unexpected medical expenses; LFEVT9= Imprisonment; LFEVT10= Bankruptcy; LFEVT11= Moving house; LFEVT12= Unexpected problems associated with the job of spouse; LFEVT 13= Others. In this case, 13 dummy variables were created. Positive responses for the experience of these events were coded (ST=1).

H3: Experiencing adverse life events has significant impact on debt behaviour

4.1.4 Socioeconomic Variables

For the list of socioeconomic variables considered, from the list of variables evaluated in the focus group study, the ones that were assigned lower levels of priority were eliminated. Systematic review findings provided additional support, and Table 23 listed commonly used variables that revealed significant effect in considerable number of studies (Chakravarty and Rhee, 1999; S. Costa, 2012; Dessart and Kuylen, 1986; Grable and Joo, 1999; Jiang et al., 2018; S. E. G. Lea et al., 1995; Nurcan and Bicakova, 2010; Ottaviani and Vandone, 2011; Rogers et al., 2015). Specifically, education, family income, income, occupational status, employment status, length of employment and social class revealed significant results in the following studies (Acquah and Addo, 2011; Brown et al., 2005; Bryan et al., 2010; Y. I. W. Chien and Devaney, 2001; Fay et al., 2002; Fogel and Schneider, 2011; Kim and DeVaney, 2001; Livingstone and Lunt, 1992; Nyhus and Webley, 2001; L. Wang, Lu, et al., 2011; Yilmazer and Devaney, 2005). From the list of variables obtained by synthesizing findings of focus group study and systematic review, those had potential of having high level of correlation with each other were eliminated. Occupational status together with occupational class were assessed together for reflecting social status of participants. This combined variable named as JOBCLASS_2. Accordingly, the following list of variables that are retained for the conceptual model can be found in Table 23.

Table 23
Socioeconomic Variables of the Conceptual Model

Variable	**Variable Description**
EDU	Education
EMPST	Employment status
JOB	Occupation
JOBCLASS	Occupational class
JOBTITLE	Title of the position (for management level)
JOBCLASS_2	Derived variable from occupational class and title of the position (JOBCLASS & JOBTITLE & JOB)
NUMDPNDT	Number of dependents
INC	Income (monthly)
WEALTH	Perceived wealth

H4a: Number of dependents has significant impact on debt behaviour

H4b: Education has significant impact on debt behaviour

H4c: Employment status has significant impact on debt behaviour

H4d: Occupational class (jobclass_2) has significant impact on debt behaviour

H4e: Income has significant impact on debt behaviour

H4f: Perceived wealth has significant impact on debt behaviour

4.1.5 Demographic Variables

Similar to previous findings of focus group, semi-structured interviews and literature review revealed that family life cycle, age, marital status and gender were commonly assessed and implemented demographic variables. Family life cycle stage was consistently determinant of probability of default in all studies it was considered, such as (Baek and Hong, 2004; Bryan et al., 2010; Dessart and Kuylen, 1986). Depending on the fact that variables of age, marital status and number of dependents encompassed by the conceptual model technically refer to life cycle stage, this parameter was not included individually.

Table 24
Demographic Variables of the Conceptual Model

Variable	Variable Description
GENDER	Gender (female / male)
AGE	Age
MARITAL	Marital status

H5a: Gender has significant impact on debt behaviour

H5b: Age has significant impact on debt behaviour

H5c: Marital status has significant impact on debt behaviour

4.1.6 Financial / Payment History Variables

Variables including number of debts, financial assets, liquid investments, credit card use patterns, number of credit cards that exceeded the spending limit, account balance, assets, number of delinquent times, number of declined credit applications, number of previously granted credits, behind schedule payments, credit limit or credit card debt to limit ratio provided enough proof of evidence regarding their influence on probability of default (Baek and Hong, 2004; Kim and DeVaney, 2001; Norvilitis et al., 2006; Rutherford and Devaney, 2009; Šušteršič et al., 2009; L. Wang, Lu, et al., 2011; L. Wang et al., 2014). 90% of the studies reviewed reported that number of credit cards was a significant indicator, while 88% of articles indicated that past credit behaviour significantly impacted on probability of default. Account balance was also an important indicator having significant influence. Synthesizing the focus group and systematic review findings, most variables were found alterations of each other which mainly aim to assess past financial behaviour of credit applicants. Some of them such as credit card use patterns were assessed under the psychological model, because of dealing with self-reported data. Accordingly, variables included in the conceptual model can be found in Table 25.

Table 25
Financial / Payment History Variables of the Conceptual Model

Variable	Variable Description
NUMCRD	Number of credit cards
OVERLCRD	Number of credit cards that exceeded the spending limit
NUMCRD_OVERLCRD	Derived variable from number of credit cards and number of credit cards that exceeded the spending limit (NUMCRD & OVERLCRD)
DEBTtoINCOME	Debt to income ratio
NREJECT_2	Number of declined credit applications
NSUCCRD_2	Number of successfully repaid credits

H6a: Number of credit cards that exceeded the spending limit (numcrd_overlcrd) has significant impact on debt behaviour

H6b: Debt to income ratio has significant impact on debt behaviour

H6c: Number of declined credit applications has significant impact on debt behaviour

H6d: Number of successfully repaid credits has significant impact on debt behaviour

4.2 Dependent Variable

Debt behaviour is a categorical variable and defined as the dependent variable for this study. A set of questions were included in order to classify participants having problematic debt behaviour. A group of questions were emphasized problematic debt repayment behaviour and the other set of questions examined problematic borrowing behaviour by focusing on accumulation of debt.

Five questions were included in order to explore debt behaviour and past constraints of participants. 1) DB1=Have you ever delayed the payment of your debt (credit card or loan repayment)? 2) DB2= Have you ever paid interest for not repaying your debt? 3) DB3=Have you ever delayed your repayment more than 90 days? 4) DB4= Have you ever gone on trial or experienced execution for your debt? 5) DB5= Have you ever experienced foreclosure for not repaying your debt? If the individual experienced at least one event (DB3, DB4, DB5), he / she was considered to have bad debt behaviour (DEBT variable=

1). Otherwise, the individual was considered to have good debt behaviour (DEBT variable= 0). For the questions DB1 and DB2, if the participants chose “always” among the reply options, he / she was considered to have bad debt behaviour (DEBT variable= 1).

Problematic borrowing behaviour was evaluated with the following questions: 1) Dcrd= What is the amount of your current credit card debt compared to your income? 2) DBTbnk= What is the amount of your current credit debt amount compared to your income? 3) DBTff= What is the amount of your current debt to your family / friends compared to your income? 4) DBTothers= What is the amount of your current debt to landlords / utility suppliers compared to your income? 5) Dtotal= What is your current debt amount compared to your income? The options to reply these question were: none; less than my monthly income; equal to my monthly income; equal to twice of my monthly income; equal to three times of my monthly income; equal to four times of my monthly income; equal to five times of my monthly income; more than five times of my monthly income.

If the participants gave one of the following responses to question Dtotal; “equal to five times of my monthly income” or “more than five times of my monthly income”, additional screening was provided with the following strategy: If the participant gave affirmative responses more than two of Dcrd, Dbnk, Dff and Dothers, and reported debt amount “equal to three times of their monthly income” or “equal to four times of their monthly income” or “equal to five times of their monthly income” or “more than five times of their monthly income” for at least two questions, they were considered having bad debt status (DEBT variable= 1).

4.3 Conceptual Models and Hypotheses

Consequently, this study mainly focuses on two group of factors including psychometric and financial perspectives. Practical purpose of this system model is to consider psychometric data in case of lack of sufficient financial and sociodemographic data that supports credit risk assessment of applicants. Hence, three separate models examining the effect of the underlying factors on debt behaviour (good / bad) were proposed. Antecedents and their impact on problematic debt behaviour were examined with the guidance of following hypotheses. Suggested research models (Figure 6,7,8) follow summary of the hypotheses shown in Table 26.

Table 26
Summary of the Hypotheses Developed

Notation	**Hypotheses**
H1a	Self-control has significant impact on debt behaviour
H1b	Conscientiousness has significant impact on debt behaviour
H1c	Emotional stability has significant impact on debt behaviour
H1d	Extraversion has significant impact on debt behaviour
H2a	Risk aversion has significant impact on debt behaviour
H2b	Attitudes towards money (power & prestige) has significant impact on debt behaviour
H2c	Attitudes towards money (retention) has significant impact on debt behaviour
H2d	Financial management behaviour has significant impact on debt behaviour
H2e	Social sanctions have significant impact on debt behaviour
H2f	Social motivation has significant impact on debt behaviour
H2g	Spending behaviour has significant impact on debt behaviour
H2h	Risky credit behaviour has significant impact on debt behaviour
H3	Experiencing adverse life events has significant impact on debt behaviour
H4a	Number of dependents has significant impact on debt behaviour
H4b	Education has significant impact on debt behaviour
H4c	Employment status has significant impact on debt behaviour
H4d	Occupational class has significant impact on debt behaviour
H4e	Income has significant impact on debt behaviour
H4f	Perceived wealth has significant impact on debt behaviour
H5a	Gender has significant impact on debt behaviour
H5b	Age has significant impact on debt behaviour
H5c	Marital status has significant impact on debt behaviour
H6a	Number of credit cards that exceeded the spending limit has significant impact on debt behaviour
H6b	Debt to income ratio has significant impact on debt behaviour
H6c	Number of declined credit applications has significant impact on debt behaviour
H6d	Number of successfully repaid credits has significant impact on debt behaviour

4.3.1 Model 1

Figure 6: Model_1

4.3.2 Model 2

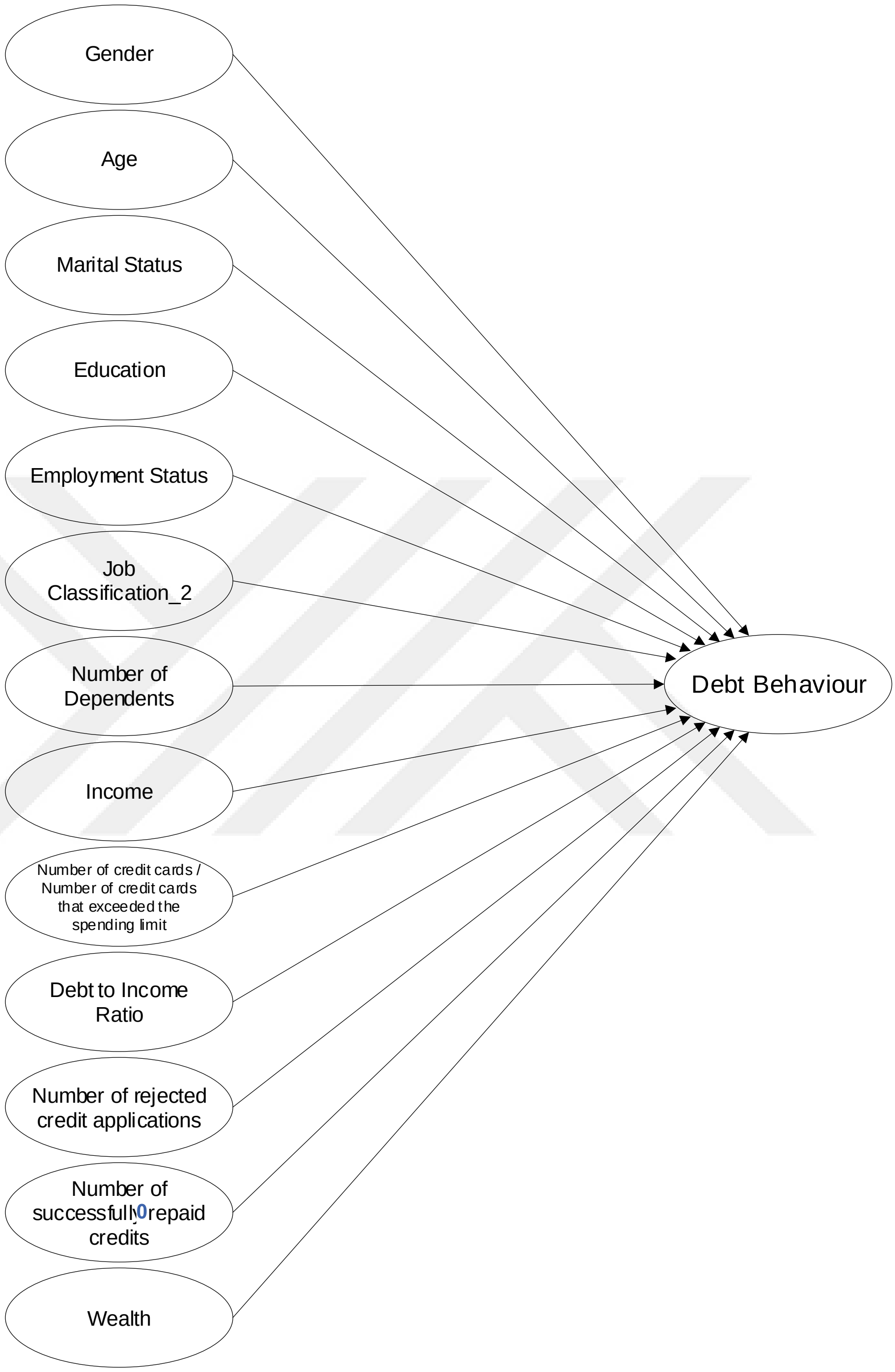

Figure 7: Model_2

4.3.3 Model 3

Figure 8: Model_3

4.4 Main Survey Design

A set of activities should be completed based on the context of the study for data collection process. According to Mazzocchi (2008), these steps comprise of determination of the sampling frame, selection of the sampling criteria, determination of the estimation technique, selection of sample size, determination of the survey administration method and cost analysis. Based on the sampling technique, steps to be applied change as in some cases sampling frame is not obtainable and identification of the reference population is not apparent.

Sampling technique applied can either be probabilistic or non-probabilistic and has great impact on cost and accuracy. Sampling technique to be used is closely related with the other conditions. For instance, when sampling frame lacks adequate information of sampling units, a stratified sampling design cannot be implemented. Administration method also depends on the sampling technique applied. Administration techniques demonstrate different levels of effectiveness and cost. These methods comprise of telephone interviews, face-to-face interviews, mail interviewing, electronic interviewing (Mazzocchi, 2008) or mixed modes (Dillman, Smyth and Christian, 2014). The rationale behind the chosen administration method and other sampling issues are explained later in detail.

4.4.1 Sampling Technique

Probability sampling and non-probability sampling are the major techniques in sampling. The main drawback of non-probability sampling is the prevention of drawing conclusions regarding the survey population. On the other hand, it is cost effective and provides quick and easy implementation. Probability sampling allows inferences and drawing conclusions depending on the survey findings. Major feature of probability sampling is that every unit within the sampling frame owns non-zero probability for being chosen and the sampling units are chosen in a random manner (National Statistics Bureau, 2018). Sampling frame is a record of whole units of the population and reference population encompasses the subjects within the scope of the researcher's interest (Mazzocchi, 2008).

The process of probability sampling is considered unbiased, but on the other hand it takes time and necessitates more effort and financial resources. In addition, a sampling frame having good quality is necessary for the implementation of probabilistic sampling (National Statistics Bureau, 2018). Some widely used strategies include simple random sampling, systematic random sampling, stratified random sampling and cluster sampling. In simple random sampling every person's chance to be within the sample is equal and probable participants are chosen by means of different techniques. In systematic random sampling, after selecting a random starting point, other respondents are chosen based on a particular sampling interval (k^{th} element). Sampling interval is identified based on the sample size. This method offers the advantages of high level of accuracy and enabling estimation of sampling errors. However, it may not detect some particular groups and there may be some biases stemming from specific sampling intervals. In stratified sampling population are grouped into sub-groups and samples are drawn from each group so as to provide representation of particular groups. These sub-groups are created depending on individuals' some common properties. Although detection of particular groups and accuracy can be provided, good knowledge of population is necessitated and estimation of sampling errors and analysing data are complicated (Burns and Kho, 2015).

Non-probability sampling techniques are mostly preferred when it is not possible or difficult to find a complete and current sampling frame or record of the individuals of the population. These techniques are less costly than probabilistic sampling techniques and several ways of intercepting people are used which makes the process fast and easy (Dillman et al., 2014). Convenience sampling, judgemental sampling and quota sampling are some common types of non-probability sampling (Mazzocchi, 2008). According to Dillman et al. (2014), all of these techniques suffer from a set of drawbacks. A great number of individuals are not taken into account and sample is mostly formed on a voluntary basis. However, according to Mazzocchi (2008) in some cases, particularly in the case of non-existence of a sampling frame non-probability sampling is the sole feasible solution and it cannot be considered biasing undoubtedly. In some cases informative nature of these techniques are not deniable.

This study used convenience sampling to choose participants of the study. Convenience sampling is a kind of non-probability sampling technique that the members are chosen based on practical concerns such as proximity, easy access or voluntary basis. Although non-probability sampling has shortcomings due to subjectivity in sample selection and representing the population, in the case of dealing with large populations it is convenient as randomization is not possible in this case (Etikan et al., 2016). One drawback of this technique is the impossibility of obtaining inferences regarding the whole population (Saunders, Lewis and Thornhill, 2009). However, as no sampling frame was available, probability sampling techniques and random sampling could not be applied for this study.

4.4.2 Sample Size

Quantitative approach and survey implementation requires the identification of the target population. Saunders et al. (2009) defines the target population as the whole cases that the sample is drawn. In some cases, due to relatively lower and feasible number of cases, it can be practical to gather data from the whole population. However, sampling constitutes a good alternative in the case of it is not practical to get data from the overall population. Additionally, sampling provides cost and time efficiency. Depending on the fact that research question for this dissertation is concerned with the individuals over the age of 18 in Turkey, a sampling frame consisting whole elements and their details cannot be obtainable. Thus, non-probability sample was drawn by applying convenience sampling approach.

Determination of sample size is driven by the level of confidence that the researcher want to achieve, accuracy (error margin) that the researcher needs for making estimations, the kind of statistical analysis to be performed and overall population’s size (Saunders et al., 2009). “Researchers normally work to a 95 percent level of certainty. This means that if your sample was selected 100 times, at least 95 of these samples would be certain to present the characteristics of the population” (Saunders et al., 2009: 218). Sekaran (2003: 293) provided population size and the corresponding sample sizes as shown in Table 27. Within the 95% confidence interval these sample sizes are appropriate for the corresponding population size.

Table 27
Population Size and Corresponding Sample Size

N	S	N	S	N	S
10	10	220	140	1200	291
15	14	230	144	1300	297
20	19	240	148	1400	302
25	24	250	152	1500	306
30	28	260	155	1600	310
35	32	270	159	1700	313
40	36	280	162	1800	317
45	40	290	165	1900	320
50	44	300	169	2000	322
55	48	320	175	2200	327
60	52	340	181	2400	331
65	56	360	186	2600	335

Continuation of Table 27

70	59	380	191	2800	338
75	63	400	196	3000	341
80	66	420	201	3500	346
85	70	440	205	4000	351
90	73	460	210	4500	354
95	76	480	214	5000	357
100	80	500	217	6000	361
110	86	550	226	7000	364
120	92	600	234	8000	367
130	97	650	242	9000	368
140	103	700	248	10000	370
150	108	750	254	15000	375
160	113	800	260	20000	377
170	118	850	265	30000	379
180	123	900	269	40000	380
190	127	950	274	50000	380
200	132	1000	278	75000	382
210	136	1100	285	1000000	384

Source: Sekaran (2003: 293)

In general, it is important to consider following criteria for sample size determination. First of all, sample sizes between 30 and 500 are convenient for most studies. When there are sub-samples and different groups, for each group minimum number of cases should be 30. Moreover, in the case of multivariate analysis techniques, for instance multiple regression, sample size should be determined by considering the number of variables to be analysed. It is recommended that sample size should be multiple times of the number of predictor (in preference at least 10 times larger) (Roscoe, 1975, as cited in Sekaran, 2003: 295). For LR, compared to multiple regression bigger sample size is necessitated, for instance sample size more than 400 is suggested by Hosmer and Lemeshow (as cited in Hair et al.,2014). Depending on the arguments above, having minimum 400 responses was aimed for this study.

4.4.3 Sample Selection

For this dissertation, target population is determined as the individuals over the age of 18 in Turkey. Turkey's population was approximately 82 million by 2018 and individuals at working age constitute 67,8% of the general population (TÜİK, 2018). The researcher because of its geographical proximity, approachability and being the region with the most intense population selected Marmara Region for the implementation of the survey. As a result of applying convenience sampling method, every individual approached by recruited surveyors was considered within the potential sample of the study.

Data collection process started at November, 2018 and in total 600 questionnaires were distributed. At the end of February 2019, by achieving a response rate of 82%, 492 responses were obtained. After data screening and elimination of questionnaires having inconsistent responses to control questions, usable 425 responses were remained. Hence, ultimate sample size of the study was 425.

4.4.4 Data Collection Method (Administration Method)

Data was gathered by means of a well-structured questionnaire and face-to-face administration method was applied in this study. Face-to-face data collection method requires high level of interaction between the interviewer and the participant. Direct interaction have impact on the quality of the responses and gives opportunity to acquire trust of participants. Questions can be answered and misperceptions can be eliminated instantly. Additionally, personal interviews can take longer (up to 30 minutes) and have remarkably higher response rates (Mazzocchi, 2008). Administration method should be established so as to improve response rate and achieve high number of completed questionnaires within budget constraints (National Statistics Bureau, 2018). Because of the length of the questionnaire and to achieve high level of response rate and good quality face-to-face interviews were conducted for implementing the questionnaires. Five interviewers were recruited and training regarding the scope of the survey, type of questions, their meanings, and goals of the study and how to answer potential respondent questions was provided.

4.5 Pilot Survey

Before the implementation of the main survey, a pilot survey was performed so as to familiarise surveyors with the implementation process, discover the reaction of respondents, anticipate whether correct information is provided by respondents and revise the sentences and words causing confusion. Before the implementation of formal pilot study, an informal pilot questionnaire was applied to nine academicians who are particularly knowledgeable on some issues regarding the quality of the questionnaire as recommended by (Dillman et al., 2014). Question orders, layout, grammatical errors and navigation complications were analysed and revised. It was also explored that the time required for the completion of the questionnaire took almost 15 minutes on average.

Formal pilot study was then implemented by the researcher and two representatives. Convenience sampling was used and questionnaires were applied on face-to-face basis so as to capture questions and feedback of respondents. Procedure applied by Ismail (2011) was followed as an implementation guideline. Information regarding the goal and content of the study, time required to complete and confidentiality of the study was provided to respondents. Voluntary nature of the participation was emphasised and some questions were asked regarding the existence of complexities and confusions in the meaning of questions. As a result of face-to-face implementation of the 60 questionnaires distributed all of them returned and 52 of them were completely responded by the participants (86.6%).

Pilot survey provided some useful comments, which were used for making the survey more understandable. Some participants commented on the phrases under "social motivation" and one item of this construct was revised based on comments so as to make the phrase clearer. Under the "social sanctions" section, the phrase of "please assume that you have debt" was added to the question for preventing misunderstanding. Before the questions of "number of previously rejected credit applications" and "number of successfully repaid credits" questions of "have you ever applied for credit" and "have you ever been granted credit" were added for making clear distinction among participants. Additionally, some items under Big Five section were revised to eliminate misunderstanding as a result of feedback of respondents. In general, respondents agreed on the layout of the questionnaire, navigation issues and meaning of items.

CHAPTER 5: QUANTITATIVE ANALYSIS & FINDINGS

5.1. Descriptive Statistics (Sample Characteristics)

In this study, demographic questions included information regarding the gender, age and marital status of participants. Additionally, socioeconomic information associated with the number of children, education, employment status, occupation, length of the current employment, occupational class, title of the position, number of dependents, home ownership status, income, family income and wealth was requested. Some information related with financial history of participants was also gathered by asking questions related with the number of credit cards and their status, status of previous credit applications and repayments, investments and savings. Some specific information was questioned so as to derive other variables and contribute to computing of new variables. Hence, the conceptual model encompassed not all of the variables. Frequencies associated with the important variables considered within the scope of the conceptual model are represented in the following tables.

65.6% of participants were male and 34.4% of participants were accounted for female. Majority of respondents were married (67.8%) and regarding the age, greatest number of respondents were between the ages of 42 and 47. Others were broken down in this fashion: 18-23 (8.9%), 24-29 (16.2%), 30-35 (18.8%), 36-41 (19.8%), 42-47 (20.2%) and over 48 (16%). 48.7% of participants were university graduates, whilst 30.8% reported that they were high school graduates. Number of primary school, secondary school graduates and respondents reported above bachelor's degree were relatively lower and close to each other. Majority of respondents were employed for a regular full time position, whilst 13.6% were self-employed. Respondents were from different occupational groups and the greatest number of respondents were workman (blue collar workers) (17.1%). Other categories representing greater number participants were civil servants, teachers, tradesman and self-employed individuals. Regarding the income level of respondents, 38.4% earned between 1.601 and 3.000 TL per month, while 31.1% reported monthly income between 3.001 and 4.500 TL. Only 1.6% of participants earned over 9.001 TL, and 18 respondents earned between 7.501 and 9.000 TL. Frequencies regarding the family income (household income) followed the similar pattern. Summary of descriptive statistics is represented in Table 28.

Table 28
Descriptives_1

Variable Code	Variable Description	Categories	Frequency (n=425)	Valid Percent%
GENDER	Gender	Male	279	65.6
		Female	146	34.4
MARITAL	Marital status	Single	137	32.2
		Married	288	67.8
AGE	Age	18-23	38	8.9
		24-29	69	16.2
		30-35	80	18.8
		36-41	84	19.8
		42-47	86	20.2
		Over 48	68	16.0
EDU	Education	Primary School	25	5.9
		Secondary School	38	8.9
		High School	131	30.8
		University (Bachelor's degree)	207	48.7
		Above Bachelor's Degree	24	5.6
EMPST	Employment status	Employed (Regular full time position)	308	72.5
		Self-employed	58	13.6
		Retired	24	5.6
		Unemployed	35	8.2
JOB	Occupation	Civil servant	57	13.5
		Workman	72	17.1
		Retired	21	5.0
		Artisan / Tradesman	51	12.1
		Self-employed	42	10.0
		Farmer	2	0.5
		Housewife	8	1.9
		Teacher	56	13.3
		Architect / Engineer	41	9.7
		Student	7	1.7
		Accountant	14	3.3
		Lawyer	1	0.2
		Bank employee	4	0.9
		Doctor	7	1.7
		Others	25	5.9
		Unemployed	14	3.3
INC	Income	Less than 1600 TL	34	8.0
		1,601 - 3,000 TL	163	38.4
		3,001 - 4,500 TL	132	31.1
		4,501 - 6,000 TL	50	11.8
		6,001 - 7,500 TL	21	4.9
		7,501 - 9,000 TL	18	4.2
		Over 9,001 TL	7	1.6

Continuation of Table 28

FAMINC	Family income	Less than 1600 TL	10	2.4
		1,601 - 4,500 TL	221	52.0
		4,501 - 7,500 TL	115	27.1
		7,501 - 10,000 TL	52	12.2
		10,001 - 13,500 TL	18	4.2
		13,501 - 15,000 TL	4	.9
		Over 15,001 TL	5	1.2
NUMDPNDT	Number of dependents	None	116	27.3
		1	42	9.9
		2	90	21.2
		3	95	22.4
		Over 4	82	19.3
HMSTATUS	Home ownership status	Home owner	210	49.4
		Rent	123	28.9
		Council house	7	1.6
		Family owned house	66	15.5
		Living with other (family or friends)	16	3.8
		Home owner & mortgage	3	0.7

Table 29 specifically focuses on occupation related variables. Some specific questions were asked associated with the job of participants. JOBCLASS_2 was derived from other questions, and it was aimed to reveal socioeconomic status and occupational class of participants. For this reason, respondents were questioned whether they were working for a managerial position. For those gave affirmative responses, extra explanation regarding the title of the job was demanded for making another classification. As a result, highest number of participants were employees (60.2%), followed by 22.1% employers and 7.1% employees at management level.

Table 29
Descriptives_2

Variable Code	Variable Description	Categories	Frequency	Valid Percent%
JOBCLASS	Occupational class (manager or not)	Yes	105	26.8
		No	287	73.2
JOBCLASS_2	Occupational class	Employer	94	22.1
		Employee	256	60.2
		Employee at management level	30	7.1
		Others	45	10.6

Continuation of Table 29

JOBDUR	Length of the current employment (years)	Less than 1 year	54	12.8
		1-5 Years	118	28.0
		6-10 Years	99	23.5
		11-15 Years	49	11.6
		Over 16 years	101	24.0

Some important indicators of financial status were questioned by means of the variable list shown in Table 30. Respondents demonstrated different credit card use patterns. Most of them had 2-4 credit cards, followed by 39.3% having only 1 credit card. 71 respondents reported that they did not have a credit card and only 0.7% of participants had 5-7 credit cards. Among those having credit card, 54.1% reported that they did not have any credit card which exceeded the spending limit. 17.9% had 1, followed by 7.5% had 2 and 3.5% had 3 credit cards that exceeded the spending limit. 29.9% of respondents never applied for credit before and 45.6% did not have previously rejected credit applications. However, 12% were declined once, followed by 9.2% that were declined 2-3 times and 3.3% that were rejected more than 4 times. Participants' perceptions regarding their own investment and savings, and also overall wealth status were also questioned. Highest number of participants announced that they had moderate level of investments and wealth (47.3% and 62.6%, respectively). Participants' debt level with regard to their income was computed from the open-ended debt questions and other categorical debt questions. 24.7% of respondents reported debt less than their monthly income, while 19.1% had debt more than ten times of their monthly income. 12.2% of participants announced debt levels more than five times of their monthly income.

Table 30
Descriptives_3

Variable Code	Variable Description	Categories	Frequency	Valid Percent%
NUMCRD	Number of credit cards	None	71	16.7
		1	167	39.3
		2-4	184	43.3
		5-7	3	0.7
OVERLCRD	Number of credit cards that exceeded the spending limit	Do not have credit card	71	16.7
		None	230	54.1
		1	76	17.9
		2	32	7.5
		3	15	3.5
		4	1	0.2

Continuation of Table 30

NUMCRD_OVERLCRD	Number of credit cards & Number of credit cards with over limit	Not have credit card	71	16.7
		1-7 credit cards & zero card with over limit	230	54.1
		1-7 credit cards & one card with over limit	76	17.9
		1-7 credit cards & two cards with over limit	32	7.5
		1-7 credit cards & more than three cards card with over limit	16	3.8
NREJECT_2	Number of rejected credit applications	I have not applied before	127	29.9
		None	194	45.6
		Once	51	12.0
		2-3 times	39	9.2
		More than 4 times	14	3.3
NSUCCRD_2	Number of successfully repaid credits	I have not applied before	124	29.2
		None	34	8.0
		Once	89	20.9
		2-3 times	119	28.0
		More than 4 times	59	13.9
INVST	Amount of investments & savings	Very bad	31	7.3
		Bad	77	18.1
		Moderate	201	47.3
		Good	110	25.9
		Very good	6	1.4
WEALTH	Perceived wealth	Very bad	11	2.6
		Bad	64	15.1
		Moderate	266	62.6
		Good	78	18.4
		Very good	6	1.4
DEBTtoINCOME	Debt to income ratio	None	71	16.7
		Less than my monthly income	105	24.7
		Equal to my monthly income	23	5.4
		Equal to twice of my monthly income	30	7.1
		Equal to three times my monthly income	32	7.5
		Equal to four times of my monthly income	13	3.1
		Equal to five times of my monthly income	18	4.2
		More than five times of my monthly income	52	12.2
		More than ten times of my monthly income	81	19.1

In order to create Logit model using zero / one dichotomous dependent variable for debt behaviour (good / bad), a set of questions were asked to respondents for categorizing debt behaviour of participants. Five questions were included in order to explore debt repayment behaviour and past constraints of participants (DBT, DBT2, DBT3, DBT4 and DBT5), and problematic borrowing behaviour was evaluated with the level of debt questions including different debt categories. Approximately 10% of participants went on trial for their debt once and 5.6% of those had that experience twice or more. Almost 5% of participants experienced foreclosure once for not repaying their debt, whilst those who had foreclosure twice or more accounted for 0.3%. Regarding the different categories of debt, around 56% of participants' credit card debt was less than their monthly income and 23.1% reported that they did not have credit card debt. Only 1.4% had credit card debt more than five times of their income. However, level of bank credit followed different pattern as 23.5% of respondents reported that they had bank credit more than five times of their monthly income. Contrarily, 45.4% of respondents announced that they did not have debt for their bank credit. Table 31 illustrates the summary of these statistics.

Table 31
Descriptives_4

Variable Code	Variable Description	Categories	Frequency	Valid Percent%
DBT1	Have you ever delayed the payment of your debt (credit card or loan repayment)?	Never	155	36.5
		Sometimes	255	60.0
		Always	15	3.5
DBT2	Have you ever paid interest for not repaying your debt?	Never	203	47.8
		Sometimes	205	48.2
		Always	17	4.0
DBT3	Have you ever delayed payment of your debt more than 90 days?	Never happened	316	74.4
		Once	56	13.2
		Twice or more	53	12.5
DBT4	Have you ever gone on trial or experienced execution for your debt?	Never happened	359	84.5
		Once	42	9.9
		Twice or more	24	5.6
DBT5	Have you ever experienced foreclosure for not repaying your debt?	Never happened	402	94.6
		Once	20	4.7
		Twice or more	3	0.7

Continuation of Table 31

DEBTLVL	Level of total debt	None	71	21.3
		Less than my monthly income	105	31.4
		Equal to my monthly income	22	6.6
		Equal to twice of my monthly income	29	8.7
		Equal to three times my monthly income	30	9.0
		Equal to four times of my monthly income	13	3.9
		Equal to five times of my monthly income	15	4.5
		More than five times of my monthly income	49	14.7
DBTcrd	Level of debt_credit card	None	98	23.1
		Less than my monthly income	236	55.5
		Equal to my monthly income	43	10.1
		Equal to twice of my monthly income	21	4.9
		Equal to three times my monthly income	12	2.8
		Equal to four times of my monthly income	7	1.6
		Equal to five times of my monthly income	2	0.5
		More than five times of my monthly income	6	1.4
DBTbnk	Level of debt_bank credit	None	193	45.4
		Less than my monthly income	63	14.8
		Equal to my monthly income	14	3.3
		Equal to twice of my monthly income	16	3.8
		Equal to three times my monthly income	16	3.8
		Equal to four times of my monthly income	14	3.3
		Equal to five times of my monthly income	9	2.1
		More than five times of my monthly income	100	23.5
DBTff	Level of debt_family & friends	None	270	63.5
		Less than my monthly income	71	16.7
		Equal to my monthly income	22	5.2
		Equal to twice of my monthly income	19	4.5
		Equal to three times my monthly income	10	2.4
		Equal to four times of my monthly income	2	0.5
		Equal to five times of my monthly income	8	1.9
		More than five times of my monthly income	23	5.4
DBTothers	Level of debt_other sources	None	364	85.6
		Less than my monthly income	56	13.2
		Equal to my monthly income	2	0.5
		Equal to twice of my monthly income	2	0.5
		More than five times of my monthly income	1	0.2

Table 32 summarizes participants’ affirmative responses to a set of adverse life events or situational factors. 242 participants never experienced one of the life events listed. 10.8% of participants linked their financial strain with the loss of job. Almost 5% stated that experiencing bankruptcy and unexpected medical expenses caused financial difficulties and repayment problems. Distribution of the positive responses to other situational circumstances were relatively lower and close to each other.

Table 32
Descriptives_5

		Responses		**Percent of Cases**
		N	**Percent**	
Responses for Adverse Life Events[a]	LFEVT_0.Never experienced one of those events	242	61.0%	65.1%
	LFEVT_1. Divorce / marital separation	1	0.3%	0.3%
	LFEVT_2. Marriage	15	3.8%	4.0%
	LFEVT_3. Spouse or child's death	4	1.0%	1.1%
	LFEVT_10. Bankruptcy	19	4.8%	5.1%
	LFEVT_5. Personal injury	10	2.5%	2.7%
	LFEVT_6. Unexpected changes of health status of a family member	15	3.8%	4.0%
	LFEVT_7. Loss of job (dismissal);	43	10.8%	11.6%
	LFEVT_8. Unexpected medical expenses	20	5.0%	5.4%
	LFEVT_11. House relocation	13	3.3%	3.5%
	LFEVT_12. Unexpected problems associated with the job of spouse	15	3.8%	4.0%
Total		397	100.0%	106.7%
a. Dichotomy group tabulated at value 1.				

5.2 Exploratory Factor Analysis (EFA) & Reliability Assessment

Factor analysis depends on the fact that original data set’s total variability can be divided into two comprising shared variability and specific variability. Factor analysis synthesizes and reduces the initial data set into small set of factors. The goals of the factor analysis include estimation of weights representing the best summary of the initial variability, anticipation of factor loadings, exploring meaningful labels and estimation of factor scores to be used for further analysis (Mazzocchi, 2008: 221)

As previously mentioned, data obtained included 12 constructs with 83 items. Items of the constructs were adopted from relevant literature. The sample size for the final survey was 425 and the total number of items were 83. Regarding the rule associated with minimum sample size for factor analysis, 5:1 criterion was taken into account. Bryant and Yarnold (1995) indicated that number of observations per variable should not be lower than 5. For the main survey data, EFA was applied to extract factors by means of applying method of principal components with Varimax rotation. Factors having (Eigen-values> 1) were extracted (Hair et al., 2014) and Kaiser-Meyer-Olkin (KMO) criterion was obtained. KMO is a measure of sampling adequacy and indicates applicability of factor analysis. Values between 0.5 and 1 indicate eligibility for factor analysis, whereas values lower than 0.5 signify that factor analysis is not appropriate for the data. In addition, communalities referring to total variance that a variable shares with the other variables are important and can be derived from factor loadings (Altunışık et al., 2012). KMO statistics having value of 0.821 represented that sample was adequate enough for factor analysis that was performed. KMO over 0.80 is accepted as “very well” (Sharma, 1996, as cited in Karagöz, 2017). In addition to KMO statistics, Bartlett Test of Sphericity that evaluates the hypothesis whether the correlation matrix is an identity matrix which represents that variables are unrelated (Karagöz, 2017) was observed. Bartlett Test of Sphericity statistics having $p < 0.05$ in this study indicated that the result of the test was statistically significant and variables were highly correlated.

Accordingly, communalities greater than 0.5 are accepted (Hair et al., 2014). In terms of factor loadings, Hair et al. (2014) stated that factor loadings over 0.5 are practically significant. According to Tabachnick and Fidell (2013) solely variables having factor loadings over 0.32 are anticipated. Loadings over 0.32, 0.45, 0.55, 0.63 and 0.71 are considered “poor”, “fair”, “good”, “very good” and “excellent”, respectively (Comrey and Lee, 1992, as cited in Tabachnick and Fidell, 2013). Hence, items having factor load less than 0.5 and items that loaded on more than one factor were deleted. As a result, 12 and related items in Table 33 were obtained for further analyses.

Reliability analysis evaluates consistency and scale properties. If a scale or test demonstrates similar findings when it is repeated under similar circumstances, this means that the scale is reliable. For reliability, the scale should consistently represent what it measures. The extent of the reliability of a scale indicates the reliability of the data obtained by means of that scale (Karagöz, 2017). Internal consistency reliability evaluates consistency of the items with each other and assess the homogeneity of the group of items measuring the same construct. One method for internal consistency is Cronbach’a Alpha which evaluates at what extent the group of items measuring a latent construct are correlated. Scale reliability is measured through Cronbach's Alpha coefficient and the highest value for the coefficient can be one (Mazzocchi, 2008). Cronbach's Alpha ≥ 0.60 represents acceptable reliability, while values over 0.80 demonstrates high level of reliability (Kalaycı, 2010; Karagöz, 2017). Hence, measurement scales included in the study generally represented high level of reliability indicating homogeneity of the set of items. Therefore, ultimate constructs and items remained for the further analysis are demonstrated in Table 33.

Table 33
Exploratory Factor Analysis and Reliability Results

Variables	Items	Factor Loadings	Cronbach's α
Social Sanctions	SOCS8. "I would feel afraid of losing my reputation in the community for going on trial"	.881	**0.940**
	SOCS2. "I would feel embarrassed for going on trial (for of not repaying) if members of my community know about it"	.880	
	SOCS7. "I would feel afraid of losing my reputation in the community for not repaying my debt"	.869	
	SOCS3. "I would feel embarrassed for exposing foreclosures (for not repaying) if members of my community know about it"	.864	
	SOCS9. "I would feel afraid of going on trial for not repaying my debt"	.860	
	SOCS1. "I would feel embarrassed for not repaying my debt if members of my community know about it"	.790	
	SOCS4. "I would feel afraid of being excluded from community for not repaying my debt"	.759	
	SOCS11. "I would feel afraid of having calls from creditors for not repaying"	.753	
	SOCS10. "I would feel afraid to be jailed for not repaying"	.725	
Risky Credit Behaviour	RC4. "I am delinquent at making payments on credit cards"	.747	**0.870**
	RC3. "I often make minimum payment on my credit card bills"	.739	
	SB7. "I often do not have enough funds to pay my credit card bills"	.739	
	FM5. "Made only minimum payments on a loan"	.713	
	FM4. "Maxed out the limit on one or more credit cards"	.708	
	RC5. "I take cash advances on my credit card"	.708	
	RC2. "I frequently use the available credit on one credit card to make payments on the other credit card"	.661	
	RC7. "I frequently have to borrow from others to make payment on my credit card bills"	.624	

Continuation of Table 33

Conscientiousness	CS6. “I work resolutely until I'm done with a job”	.829	**0.852**
	CS7. “I work efficiently”	.795	
	CS3. “I am a trustworthy person to be responsible from a task (work, homework, job)”	.743	
	CS8. “I plan and apply these plans”	.701	
	CS1. “I put effort to do any work completely”	.644	
Spending Behaviour	SB4. “I often buy things to make myself better”	.803	**0.831**
	SB5. “I feel restless on days when I do not get to shop”	.776	
	SB2. “I buy without thinking its consequences”	.745	
	SB1.” If I have money at the end of the month, I have to spend it”	.665	
	SB3. “I often buy things even though I could not afford them”	.579	
Money Attitudes (Power & Prestige)	PP3. “I own nice things in order to impress others”	.850	**0.805**
	PP2. “I admit I purchase things to impress others”	.839	
	PP1. “I use money to influence people to do things for me”	.707	
	PP5. “I sometimes boast about how much money I have”	.641	
	PP4. “I behave as if money is the ultimate symbol of success”	.627	
Extraversion / Introversion	EX8. “I am a silent person”	.790	**0.777**
	EX1. “I am a talkative person”	.766	
	EX6. “I am an outgoing, social person”	.706	
	EX2. “I am an introvert person”	.677	
	EX7. “Sometimes I am shy”	.502	
Money Attitudes (Retention)	RT2. “I put money aside on a regular basis for the future”	.764	**0.821**
	FM6. “Began or maintained an emergency savings fund”	.737	
	FM7. “Saved for a long-term goal (buying car, education, home etc.)”	.717	
	RT3. “I save now to prepare for my old age”	.689	
Neuroticism	NR3. “I am a nervous person”	.835	**0.751**
	NR4. “I am an anxious person”	.723	
	NR6. “My mental state quickly changes”	.665	
	NR8. “I can easily get angry”	.647	
	NR1. “I'm a pessimist, sad person”	.528	
Social Motivation	SM2. “My friends and family think I should be responsible in using credit or borrowing money”	.871	**0.808**
	SM1. “Most people who are important to me think I should be responsible in using credit or borrowing money”	.853	
	SM3. “I want to do what my family and friends think I should do regarding credit and borrowing money”	.718	
Financial Management	FM1. “Paid all my bills on my bills on time”	.711	**0,745**
	FM2. “Kept a written or electronic record of my monthly expenses”	.708	
	FM3. “Stayed within my budget or spending plan”	.670	

Continuation of Table 33

Self-Control	SC2. “I do things that feel good in the moment but regret later on”	.748	**0,722**
	SC1. “I have a hard time breaking bad habits”	.734	
	SC4. “I often act without thinking through all the alternatives”	.607	
Risk Aversion	RA3. “I would not describe myself as a risk-taker”	.754	**0,594**
	RA2. “I prefer a routine way of life to an unpredictable one full of change”	.723	
	RA1. “I tend to avoid talking to strangers”	.573	

*Kaiser-Meyer-Olkin Measure of Sampling Adequacy: ,821

Items for the social sanctions construct were obviously loaded on one factor and only two items were deleted due to low factor loadings. Regarding the risky credit behaviour, RC2, RC3, RC4, RC5 and RC7 were loaded on a single factor. Some items for financial management and spending behaviour were also loaded under this factor. This is an acceptable case as the constructs of risky credit behaviour, financial management and spending behaviour were theoretically related. Big Five constructs including conscientiousness, neuroticism and extraversion / introversion items were perfectly loaded to the associated factors. Factor loadings less than 0.5 were deleted. Items for the spending behaviour SB1, SB2, SB3, SB4 and SB5 were loaded on a single factor, while SB7 (“I often do not have enough funds to pay my credit card bills”) was loaded under another factor with the items of risky credit behaviour. From the items of money attitudes (power & prestige) PP1, PP2, PP3, PP4 and PP5 were remained due to loading on one factor and PP6 (“I spend money to make myself better”) was omitted because of low factor loading. Three items representing extraversion / introversion were omitted. Two items for the financial management FM6 and FM7 were found to be correlated with RT2 and RT3 which demonstrated retention aspect of money attitudes. Items were meaningfully and theoretically correlated with each other. NR3, NR4, NR6, NR8 and NR1 were remained due to factor loadings over 0.5 and they were correlated with each other. All items of the original “social motivation” construct were loaded on a single factor with excellent factor loadings (over 0.71). Regarding the financial management construct, FM1, FM2 and FM3 were loaded on a single factor, while the others were found correlated with the items of money attitudes (retention) and risky credit behaviour. The items were combined meaningfully under associated factors and this was not an unexpected situation as some questions were asked for control purposes and the arguments in the relevant literature support their relevance. From the self-control construct SC3 and SC5 were subject to deletion, as SC5 included a control question and SC3 demonstrated low factor loading. From the original construct of risk aversion, RA1, RA2 and RA3 were remained for further analysis.

Table 34 shows the total variance explained, initial eigenvalues and values after extraction. Findings demonstrated that twelve factors obtained with principal component analysis extraction method. First factor explained 10.971%, second factor explained 7.944%, third factor explained 5.645% and fourth factor explained 5.521% of the total variance. Cumulative variance explained was 64.199% of the total variance.

Table 34
Total Variance Explained

Total Variance Explained									
Component	Initial Eigenvalues			Extraction Sums of Squared Loadings			Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8.383	14.453	14.453	8.383	14.453	14.453	6.363	10.971	10.971
2	6.788	11.703	26.157	6.788	11.703	26.157	4.608	7.944	18.915
3	4.114	7.094	33.250	4.114	7.094	33.250	3.274	5.645	24.561
4	3.415	5.888	39.138	3.415	5.888	39.138	3.202	5.521	30.082
5	2.852	4.918	44.056	2.852	4.918	44.056	3.197	5.512	35.594
6	2.403	4.143	48.199	2.403	4.143	48.199	2.813	4.850	40.444
7	1.974	3.404	51.602	1.974	3.404	51.602	2.787	4.805	45.249
8	1.762	3.039	54.641	1.762	3.039	54.641	2.753	4.746	49.995
9	1.556	2.682	57.323	1.556	2.682	57.323	2.388	4.118	54.112
10	1.514	2.610	59.933	1.514	2.610	59.933	2.103	3.625	57.738
11	1.299	2.239	62.172	1.299	2.239	62.172	1.973	3.401	61.139
12	1.176	2.027	64.199	1.176	2.027	64.199	1.775	3.061	64.199
Extraction Method: Principal Component Analysis.									

5.3 Logistic Models and Assessment of Fitness

The objective of this study is to construct a credit scoring model for supporting credit granting decisions. In order to establish efficient alternatives in discriminating individuals with high level of credit risk, models based on Logistic Regression were constructed. As aforementioned before in previous chapters, various techniques exist for classifying individuals belonging to good or bad group in terms of credit risk. Logistic Regression provides prediction of group membership by means of a group of independent variables and provides predictions regarding the occurrence of the event of interest (Hair et al., 2014). The group of independent variables can be either continuous or categorical, and binary LR produces the probability regarding the belonging to a specific group for each observation (Tabachnick and Fidell, 2013). According to Hair et al. (2014) LR is good suited for determining the set of independent variables that influence predicting group memberships and for constructing a decision support mechanism for classification purposes.

Lee, Chiu, Chou and Lu (2006) indicated that Discriminant Analysis and LR are widely utilised statistical techniques in constructing decision support systems for credit scoring. However, LR allows dichotomous outcome variable in contrast to DA (Yap et al., 2011; H. A. Abdou and Pointon, 2011: 71). Discriminant Analysis allows only metric independent variables and requires normal distribution of independent variables. Nevertheless, LR does not necessitate assumptions of DA (Karagöz, 2017). Additionally, linear relationship between variables is not essential in contrast to multiple regression and nonlinear impacts can be observed due to logistic function (Hair et al., 2014). A wide range of papers implemented Logistic Regression for constructing credit scoring models or discriminating risky individuals (H. Abdou et al., 2008; Akben-Selcuk, 2015; Costa, 2012; Domowitz and Sartain, 1999; Ge et al., 2017; Kočenda and Vojtek, 2011; Masyutin, 2015; Mewse et al., 2010; Perry, 2008; Rogers et al., 2015; Rutherford and Devaney, 2009; Stone and Maury, 2006; von Stumm et al., 2013; J. Wang and Xiao, 2009; Ganzach and Amar, 2017).

5.3.1 Model Design

LR allows binary outcomes or categorical dependent variables. Multinomial Logistic Regression handles multinomial dependent variables and in the case of existence of more than two categories, this type of regression can be used instead of binary LR (Mazzocchi, 2008). Generally, LR offers the analysis regarding the set of independent variables that predict the outcome. Impact of the variables on the probability of the outcome (increase / decrease / no impact) and at what extent a particular independent variable contribute to the probability of group membership can be observed by means of LR models (Tabachnick and Fidell, 2013). Logistic function having value between 0 and 1 evaluates the level of risk. Hence regarding the research design, binary dependent variables (0 and 1) demonstrate two different groups within the scope of the investigation. Allocation of the values to groups can be done randomly, however this is important in case of anticipating model coefficients. Another design issue is associated with sample size. For LR, compared to multiple regression bigger sample size is necessitated, for instance sample size more than 400 is suggested by Hosmer and Lemeshow (as cited in Hair et al.,2014).

5.3.2 Model Estimation and Interpretation of Coefficients

In this study, the discrete outcome was debt behaviour (good / bad) that represents credit risk of individuals. DEBT was a binary variable, and according to past financial constraints, credit repayment behaviour and debt accumulation questions individuals were classified as good or bad in terms of creditworthiness. LR is considered a prevalent classification technique within the machine learning area. Applicants' creditworthiness can be defined as the outcome variable and the probabilities (P) from the logistic equation represented by Eq.1 is utilised to discriminate individuals having high risk from good applicants (Huo et al., 2017). The formula represents logistic regression model with multiple independent variables.

$$Z = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots \beta_n X_n \qquad \text{Eq.1}$$

In the case of parameter estimates, generally maximum likelihood method is utilised. Negative or positive β coefficients of the independent variables in the model demonstrates the direction of the relationship. Positive coefficients represent that probability of the occurrence of the interested event will increase, while negative coefficients serve to decrease the probability of the occurrence of the interested event. P(Y) represents the probability of occurrence of the interested event and Q(Y) represents the probability of non-occurrence of that event. Calculation of the model coefficients is performed as in Eq.2 (Karagöz, 2017).

$$\frac{P(Y)}{Q(Y)} = \frac{P(Y)}{1-P(Y)} = \frac{\frac{e^Z}{1+e^Z}}{1-\left(\frac{e^Z}{1+e^Z}\right)} = e^z = e^{\beta_0+\beta_1 X_1+\beta_2 X_2+\beta_3 X_3+\cdots\beta_n X_n} \qquad \text{Eq.2}$$

LR mainly depends on "odds ratios" which compares the probability of occurrence of the interested event with the probability of the non-occurrence. As presented in Eq.2, LR model is constructed by estimating the natural logarithm of odds ratio (Eq-3,4).

$$\text{Odds Ratio} = \frac{P(Y)}{Q(Y)} = e^z = e^{\beta_0+\beta_1 X_1+\beta_2 X_2+\beta_3 X_3+\cdots\beta_n X_n} = Exp(\beta) \qquad \text{Eq.3}$$

$$\ln\left(\frac{P}{1-P}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots \beta_n X_n \qquad \text{Eq.4}$$

Parameters of the LR model is obtained by means of Maximum Likelihood method (Kalaycı, 2010). $Exp(\beta)$ value for each parameter or odds ratio demonstrates at what extent odds of belonging to one class of the outcome variable change with one unit increase in a particular independent variable. Natural logarithm of the odds ratios produces "β" coefficients. Hence, one unit change in the independent variable causes multiplication of odds by $Exp(\beta)$ (Tabachnick and Fidell, 2013).

Odds ratio greater than one indicates that (in the case of statistical significance) predictors substantially contribute to the change in the dependent variable. In this case, the predictor is an important risk factor. If the value of odds ratio is close to zero, the predictor is still considered a risk factor. However, in this case the predictor has a negative impact on the dependent variable which causes lower probabilities. Hence, positive β coefficient represents that odds ratio is higher than one and probability is greater than 0.50 (50%). Contrarily, negative β coefficient indicates that odds ratio is lower than one and the probability is less than 0.50 (50%). Generally, critical value is set to 0.50 and outcome category is defined according to this cut-off value. If the predicted probability is over 0.50, estimated outcome variable becomes one (the event of interest occurred), otherwise it becomes zero (the event of interest did not occur) indicating the group membership of the observation (Karagöz, 2017; Hair et al., 2014). According to Hair et al. (2014) conclusions regarding the coefficients can be drawn as follows: Positive or negative influences of the predictors can be assessed by means of β coefficients, and $Exp(\beta)$ value bigger than one also indicate positive impact. Degree of the change in the outcome variable is best evaluated by means of $Exp(\beta)$, and is estimated by the following formula (Eq.5).

$$Percentage\ change = (\ Exp(\beta) - 1)\ X\ 100 \qquad \text{Eq. 5}$$

5.3.3 Evaluation of the Goodness of Fit for the LR Model

Model estimation fit is assessed by means of the value of "-2 Log likelihood", and alterations in the model fit can be anticipated by observing this value. Lower "-2 Log likelihood" values indicate improved model fit. Chi-square test is utilised to anticipate decrease in Log likelihood statistics, and statistical significance of this test is important. However, drawing consequences regarding the model fit should not be done merely on the Chi-square statistics (Hair et al., 2014). Statistical significant findings ($p < 0.05$) for Omnibus Tests demonstrate that model coefficients are statistically significant and contribute to explain the dependent variable. This means independent variables have influence on the dependent variable (Karagöz, 2017). Along with these tests, various measures exist for interpreting general model fit. For instance, "Cox & Snell R Square" and "Nagelkerke R Square" measures give information regarding the model fit as well. These statistics indicate to what extent independent variables explain the overall change in the dependent variable (Karagöz, 2017).-

From the aspect of prediction efficiency, model fit can be anticipated based on classification tables and Chi-square based "Hosmer and Lemeshow Test" which classifies cases by splitting into ten (10) groups, and for each group the test compares the truly existing events and their predictions by means of Chi-square value. The less the differences, the model shows better fit with the sample (Hair et al., 2014). According to this statistical test, non-significance of Chi-square statistics ($p > 0.05$) is required for goodness of fit (Tabachnick and Fidell, 2013). Another measure for predictive accuracy and model fit is the classification table which demonstrates to what extent group membership is forecasted by means of estimated probabilities (Karagöz, 2017). Percentage of cases that are correctly allocated to the groups refers to "hit ratio" (Hair et al., 2014).

5.3.4 Model_1

This model incorporates psychological and situational variables in order to find best set of predictors discriminating individuals' level of credit risk so as to construct a psychometric credit scoring mechanism. In the quantitative analysis, survey data of 425 individuals was used. Dependent variable, debt behaviour was a binary variable that was coded one (1) for individuals having problematic debt behaviour (bad), and zero (0) for individuals having good debt behaviour. The impact of the following variables were observed: Experience of adverse life events (ST=1 for positive responses; ST=0 for negative responses), social sanctions, risky credit behaviour, conscientiousness, spending behaviour, attitudes towards money (power & prestige), extraversion / introversion, attitudes towards money (retention), neuroticism, social motivation, financial management, self-control and risk aversion. As a result of data screening and elimination of outliers, ultimate number of observations was 419 which was demonstrated Table 35 In the case of LR application procedure, “enter” method evaluating the significance of regression coefficients at one step in contrast to stepwise approach (Karagöz, 2017) was utilised.

Table 35
Case Processing Summary Model_1

Unweighted Cases[a]		N	Percent
Selected Cases	Included in Analysis	419	99.8
	Missing Cases	1	.2
	Total	420	100.0
Unselected Cases		0	.0
Total		420	100.0

Table 36 indicates how the sample was divided into groups to predict the differences among individuals. Initial classification was performed based on responses to a set of questions reflecting debt & credit behaviour (borrowing / repayment) of individuals. The beginning classification table demonstrates the classification results without including independent variables and solely takes constant into consideration. This is considered as the reference table for comparison of the model and its ultimate classification performance.

Table 36
Beginning Classification Table Model_1

	Observed		Predicted		
			DEBT.Debt behaviour		Percentage Correct
			GOOD	BAD	
Step 0	DEBT.Debt behaviour	GOOD	314	0	100.0
		BAD	105	0	.0
	Overall Percentage				74.9
a. Constant is included in the model.					
b. The cut value is ,500					

Table 37 indicates that Chi-square values were statistically significant ($p < 0.05$) for Omnibus Tests, which reveals that model coefficients were statistically significant and contributed to explain the dependent variable.

Table 37
Omnibus Tests of Model Coefficients Model_1

		Chi-square	df	Sig.
Step 1	Step	209.876	13	.000
	Block	209.876	13	.000
	Model	209.876	13	.000

Table 38 includes another indicator of model fit and shows overall model fit. Independent variables included in the model explains 39.4% and 58.3% of the change in the dependent variable according to “Cox & Snell R Square” and “Nagelkerke R Square”, respectively.

Table 38
Model Summary Model_1

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	261.909[a]	.394	.583

Another goodness of fit indicator “Hosmer and Lemeshow Test” represents the fitness between model and sample. According to the results in Table 38, non-significance of Chi-square statistics ($p > 0.05$) revealed goodness of fit.

Table 39
Hosmer and Lemeshow Test Model_1

Step	Chi-square	df	Sig.
1	7.946	8	.439

Coefficients of the model can be interpreted as follows: In the case of positive coefficient (β), Exp (β) value will be more than one (1) indicating improvement in odds in the case of positive alteration in the outcome variable. In contrast, negative coefficients cause Exp (β) values less than one (1) which means decrease in odds. Numeric value of the coefficients represent the degree of change in the probability when there is one-unit change in the predictor. Interpretation of the coefficients change according to type of the predictor, as non-metric variables require different approach. Change in probability in the case of one-unit change in the predictor is estimated by the following formula as aforementioned before.

$$Percentage\ change = (\ Exp(\beta) - 1)\ X\ 100 \qquad \text{Eq.5}$$

Positive β coefficients indicated increase in the probability of credit risk as the original coefficients were represented in terms of logit values. In contrast, negative β coefficients represented decrease in credit risk. When results for 13 predictor variables were examined, it was observed that 7 variables including ST, risky credit behaviour, conscientiousness, neuroticism, social motivation, financial management and risk aversion were statistically significant ($p < 0.05$). Hence, 7 variables significantly contributed to the explanation of the dependent variable. Multicollinearity among variables was also checked as LR procedure is influenced by multicollinearity. Depending on the fact that, correlation matrix did not reveal high correlations (higher than 0.80) among independent variables, the variables were considered as candidates for inclusion in the model.

According to prediction results for LR model, among independent variables ST, risky credit behaviour, neuroticism and social motivation with positive β values and Exp (β) greater than 1 indicated that these independent variables had effect on increase in credit risk. On the other hand, conscientiousness, financial management and risk aversion with negative β values and Exp (β) less than 1 demonstrated that these variables had impact on decrease in credit risk.

Exp (β) column gives odds ratios that present comparative importance of independent variables on the odds of dependent variable. For instance, Exp (β) value for risky credit behaviour was 2.749 representing that this factor almost 3 times increased credit risk. Hence, risky credit behaviour is an important factor in creditworthiness decisions. Another important factor enhancing credit risk was neuroticism with Exp (β) value of 1,992. This means that, one-unit change in neuroticism score of individuals approximately 2 times increases credit risk. Regarding the social motivation, Exp (β) value of 2.240 revealed that, this factor enhanced credit risk almost 2 times.

Among factors causing decrease in credit risk, risk aversion with Exp (β) value of 0,681 indicated that one-unit increase in risk aversion score almost 0.7 times decreased credit risk. Conscientiousness and financial management had close magnitude of influence with Exp (β) values of 0.593 and 0.444, respectively. Hence, increase in conscientiousness and financial management abilities multiplies the odds by 0.593 and 0.444. This means that one-unit increase in conscientiousness will approximately decrease the odds by 40%, while one-unit increase in financial management will almost decrease the odds by 60%.

ST is a dummy variable representing experience of adverse life events (ST=1 for positive responses; ST=0 for negative responses). When dummy variables are utilized, reference category is chosen, and relative degree of change in the outcome for the represented category compared to reference category is assessed though Exp (β) value (Hair et al., 2014). In this case, reference category is set as the group did not experience adverse life events, and Exp (β) of situational factors (ST) demonstrates the percentage of odds ratio in the case of presence of situational factors compared to reference category (ST=0 for negative responses). Hence, bad credit status was 22.441 times more likely to occur in the case of experience of adverse life events compared to participants that have not experienced. Situational factors, therefore had considerable impact on discriminating individuals with high credit risk (Table 40).

Table 40
Variables in the Equation Model_1

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B) Lower	95% C.I.for EXP(B) Upper
Step 1[a]	**ST(1)**	**3.111**	**.399**	**60.802**	**1**	**.000***	**22.441**	**10.267**	**49.050**
	Social Sanctions	-.217	.174	1.547	1	.214	.805	.572	1.133
	Risky Credit Behaviour	**1.011**	**.237**	**18.151**	**1**	**.000***	**2.749**	**1.726**	**4.377**
	Conscientiousness	**-.522**	**.247**	**4.485**	**1**	**.034***	**.593**	**.366**	**.962**
	Spending Behaviour	-.080	.241	.110	1	.740	.923	.576	1.480
	Attitudes towards Money (Power & Prestige)	-.201	.245	.672	1	.412	.818	.505	1.323
	Extraversion / Introversion	-.196	.238	.679	1	.410	.822	.515	1.311
	Attitudes towards Money (Retention)	-.111	.194	.324	1	.570	.895	.612	1.310
	Neuroticism	**.689**	**.213**	**10.509**	**1**	**.001***	**1.992**	**1.313**	**3.022**
	Social Motivation	**.807**	**.208**	**15.002**	**1**	**.000***	**2.240**	**1.490**	**3.370**
	Financial Management	**-.813**	**.255**	**10.177**	**1**	**.001***	**.444**	**.269**	**.731**
	Self -control	-.042	.198	.046	1	.831	.959	.650	1.413
	Risk Aversion	**-.384**	**.190**	**4.094**	**1**	**.043***	**.681**	**.469**	**.988**
	Constant	-1.068	1.687	.401	1	.526	.344		

* Coefficients significant at $p<0.05$

Table 41 represents number of cases accurately predicted. Overall prediction accuracy of the model was 86.2% which means model successfully predicted 86.2% of the cases. When compared with the beginning block representing 74.9% classification performance, there was considerable improvement in prediction accuracy. Percentage of true negatives (event that is not in major scope of interest) which is the ratio of accurately predicted as good cases was 91.4% which is also called specificity. This model predicted 91.4% of individuals having good credit risk successfully. Sensitivity of the model was 70.5%, which represents true positives demonstrating the percentage of individuals classified as having bad credit risk (event of interest) accurately. Model classified 70.5% of individuals with high credit risk accurately. Consequently, hypotheses including H1a, H1b, H1c, H1d, H2a, H2b, H2c, H2d, H2e, H2f, H2g, H2h and H3 were tested in this model and H1b, H1c, H2a, H2d, H2f, H2h and H3 were accepted.

Table 41
Final Classification Table Model_1

	Observed		Predicted		
			DEBT.Debt behaviour		Percentage Correct
			GOOD	BAD	
Step 1	DEBT.Debt behaviour	GOOD	287	27	91.4
		BAD	31	74	70.5
	Overall Percentage				86.2
a. The cut value is .500					

5.3.5 Model_2

This model integrates financial, demographic and socioeconomic variables in order to explore best combination of predictors discriminating applicants with high level of risk for establishing a credit scoring model. These predictors are usually utilized for constructing conventional credit scoring systems with financial data and past financial behaviour. As the decision support system proposed has two components including psychometric and financial, this part of analysis is supposed to support financial module by revealing predictors with most exploratory power. There were some limitations associated with this set of predictors as they were based on self-reported data. Some variables were derived from each other such as debt to income ratio (DEBTtoINCOME) and occupational class (JOBCLASS_2).

Occupation information, occupational class (manager or not) and title of the position were used for creating the variable JOBCLASS_2. Categories for the classification were as follows: (1) Employer, (2) Employee, (3) Employee at management level, (4) Others. Ratio of number of credit cards to number of credit cards with exceeded limit (NUMCRD_OVERLCRD) was also derived from other variables (NUMCRD and OVERLCRD). Categories were as follows: (1) Not have credit card, (2) 1-7 credit cards & zero card with over limit, (3) 1-7 credit cards & one card with over limit (4) 1-7 credit cards & two cards with over limit (5) 1-7 credit cards & more than three cards card with over limit. Number of rejected and successfully repaid credits were represented by NREJECT and NSUCCRD variables. Categories were coded as follows: (1) I have not applied before, (2) None, (3) Once, (4) 2-3 times, (5) More than 4 times. Other variables were composed of income (monthly) (INC), number of dependents (NUMDPNDT), employment status (EMPST), education (EDU) and perceived overall wealth status (WEALTH). Regarding the demographic variables, gender (GENDER), age (AGE) and marital status (MARITAL) were incorporated for the conceptual model. At the end, testable LR model had 13 variables representing financial, demographic and socioeconomic information of applicants. Dependent variable, debt behaviour was the same as the one used for the previous analysis that was coded one (1) for individuals having problematic debt & credit behaviour (bad), and zero (0) for individuals having good debt & credit behaviour. The same data set was used for the analysis (425 observations). Data screening and elimination of outliers provided a data set with 418 cases. LR application procedure again utilized “enter” method (Table 42).

Table 42
Case Processing Summary Model_2

Unweighted Cases[a]		**N**	**Percent**
Selected Cases	Included in Analysis	418	100.0
	Missing Cases	0	.0
	Total	418	100.0
Unselected Cases		0	.0
Total		418	100.0

Table 43 represents a reference table for comparison with the ultimate model performance. This table gives prediction results without independent variables and only constant is included in the initial model. According to this, initial classification accuracy was 75.6%, which indicated that 75.6% of the participants were classified accurately. Any performance improvements can be observed by comparing classification performances in the case of independent variables consideration.

Table 43
Beginning Classification Table Model_2

	Observed		**Predicted**		
			DEBT.Debt behaviour		**Percentage Correct**
			GOOD	BAD	
Step 0	DEBT.Debt behaviour	GOOD	316	0	100.0
		BAD	102	0	.0
	Overall Percentage				75.6
a. Constant is included in the model.					
b. The cut value is .500					

Table 44 represents Omnibus Tests' results for evaluating goodness of fit. Statistically significant ($p < 0.05$) Chi-square values indicated that model coefficients were statistically significant, and independent variables contributed to explain the dependent variable.

Table 44
Omnibus Tests of Model Coefficients Model_2

		Chi-square	df	Sig.
Step 1	Step	379.116	51	.000
	Block	379.116	51	.000
	Model	379.116	51	.000

The following model summary output corresponding to Table 45 represents overall model fit. Based on "Cox & Snell R Square" independent variables of the model explained 59,6% of the change in the dependent variable, and according to "Nagelkerke R Square" 88,9% change in the dependent variable was explained by independent variables.

Table 45
Model Summary Model_2

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	85.423[a]	.596	.889

According to "Hosmer and Lemeshow Test" indicating to what extent model fits with the sample, ($p > 0.05$) revealed insignificant results for Chi-square statistics which implies good fit between model and sample.

Table 46
Hosmer and Lemeshow Test Model_2

Step	Chi-square	df	Sig.
1	3.757	8	.878

According to the prediction results of LR model applied for financial, demographic and socioeconomic indicators of applicants, six variables were statistically significant and contributed to the explanation of debt behaviour as observed in Table 47. Hence, the dependent variable can be predicted by means of six predictors. Hence, the proposed model was established based on those six variables and classification was performed again.

These variables were comprised of gender, education, occupational class (composite variable derived from occupation information), debt to income ratio, number of previously rejected credits and perceived wealth. As the whole variables were categorical, different categories and their comparison with the reference category revealed different results. Impact of each category was interpreted with regard to reference category. In this case, gender involved dummy coding and male group was chosen as the reference category. Hence, coefficients of this dummy variable indicated the change in the dependent variable for the represented category compared to reference category (GENDER=0 for men; GENDER=1 for women). Exp (β) coefficient of gender variable demonstrates the percentage of odds ratio in the case of being female compared to reference category. Thus, bad credit status was almost 532 times more likely to occur in female group compared to male group. Gender, therefore had remarkable impact on discriminating individuals with high level of risk.

Education was another significant indicator ($p < 0.05$) and primary school graduates was defined as the reference category. According to findings, being a secondary school graduate decreased credit risk almost 0.2 times (Exp (β)=0,170). Coefficient indicated the sign that was previously expected. However, no significant differences were observed when the level of education increased. Merely, being secondary school graduate decreases credit risk compared to primary school graduates. However, further investigation revealed that most of the primary school graduates (40%) were employers and employees working for a regular full time job was mostly formed (46%) of the secondary school graduates. Although employers reported higher level of income (all of the participants having 7501-9000 TL monthly income and 60% of them with monthly income higher than 9001 TL were employers), occupational class was an important indicator in terms of signalling risky behaviour. For instance, occupation information, occupational class (manager or not) and title of the position were used for creating the variable JOBCLASS_2 which was found as another significant predictor ($p < 0.005$). Based on findings, compared to being an employer, credit risk 0.002 times decreased in the case of being an employee and 0.0005 times decreased for employees at management level. Odds ratios did not indicate a high level of discriminating power for this variable. However, being in the employee group or working in a management position increased the probability of being in good credit risk group compared to employers. Hence, probability of high risk of primary school graduates can be attributed to high number of employers among this group.

DEBTtoINCOME ratio was found as a significant indicator of debt behaviour ($p < 0.05$), and participants having higher debt to income ratio had greater odds for credit risk in comparison to those reported that they did not have any debt (reference category). Participants reported that their overall debt was almost 4 times of their monthly income had greater odds for bad credit risk compared to those did not have any debt. Credit risk was almost 243 times higher for this group. Participants reported that their overall debt was almost 5 times of their monthly income had greater odds and credit risk was almost 258 times higher for this group. In the case of participants who reported overall debt more than 5 times of their monthly income and more than 10 times of their monthly income, odds ratios were far greater. Especially, those who reported overall debt more than 10 times of their monthly income were constituted the individuals with highest credit risk.

Number of rejected credits of the respondents was also explored as a significant indicator of credit risk ($p < 0.001$). Participants reported one rejected credit application were more likely to be in bad credit group compared to participants reported that they did not have any credit application before. In the case of participants reported 2-3 rejected credit applications, odds of credit risk was higher. For participants who reported that they had 4 rejected credit applications, β coefficient was extremely high indicating that this group of individuals carries the highest risk in terms of debt behaviour. Hence, Exp (β) value (over one million) indicated that the probability of being in the bad credit risk group extremely increased when applicants reported more than 4 rejected credit applications compared to those did not apply for credit before. Further analysis indicated that 57.1% of this group (over than 4 rejected credit applications) stated that they were self-employed or artisan (tradesman). Also, among respondents reported 2-3 rejected credit applications 68.4% of them were self-employed or artisan (tradesman). On the other hand, crosstabulation results for number of successfully repaid credits based on occupational groups presented that within the respondents with 2-3 successfully repaid credits the highest number of individuals were (62.6%) employees with full time jobs including white and blue collar workers and civil servants. Only 21.7% of self-employed or artisans reported 2-3 successfully repaid credits. However, among group with over 4 successfully repaid credits, 50% of them were self-employed or artisans indicating requirement for financial resources in the case of managing business. Single traders and limited company owners were included in the sample and pressure of the costs of maintaining the business might result financial strain and struggling. Hence, this group also applies for huge amount business loans in addition to personal loans. Company assets and potential of the business make them target customers for banks which result in easy access to loan opportunities. Most of the debt burden can be associated with business costs. Macroeconomic conditions and market fluctuations making them more vulnerable usually put obstacles in the case of meeting liabilities against creditors. In this case, another debt resources are investigated in order to maintain business which makes debt burden much more problematic. Detailed analysis on data set of this study revealed that among self-employed participants 44.7% reported that their debt was more than 10 times of their monthly income, while among employees for a full time job merely 14.9% reported such a high level of debt. Based on findings aforementioned before, compared to being an employer, credit risk decreased in the case of being an employee. From another aspect, among self-employed almost 64% stated that they experienced adverse life events, while 31.2% of full time employees indicated experience of adverse life events associated with their financial strain. Hence, being self-employed and having more number of rejected credit applications might increase the probability of being in bad credit risk status.

Perceived wealth had significant impact on debt behaviour ($p < 0.001$). Reporting moderate wealth status decreased the credit risk compared to respondents who perceived their wealth status very bad. For change in the wealth status from moderate to very bad 11.960 unit decrease was expected in the log odds of the dependent variable (β coefficient represents the change in log odds comparing moderate to very bad wealth status group). Also, participants stated that their wealth status was good was more likely to be in the good credit risk group compared to respondents who perceived their wealth status very bad. Similarly, for change in the wealth status from good to very bad 12.166 unit decrease was expected in the log odds of the dependent variable (β coefficient represents the change in log odds comparing good to very bad wealth status group). Exp (β) values or odds ratios less than 1 presented low level of risk decrease for the studied group compared to reference group. Exp (β) values less than .00005 indicated that reporting good or moderate wealth status increased the probability of being in the good credit risk group very slightly compared to participants perceived their wealth status very bad.

Regarding the responses to the question associated with level of investments, participants with moderate level of investments were mostly employees with a full time job (75.1%). On the other hand, 18.8% of self-employed reported that they had moderate level of investments. Among self-employed almost 33% and among employees almost 27.7% announced that their level of investments were good or very good. Hence, the impact of the indicator wealth was probably associated with debt burden or low level of income differing among these groups. For instance, 66.7% of respondents perceived their overall wealth status very good reported that their debt level was less than their monthly income.

Table 47
Variables in the Equation Model_2

								95% C.I.for EXP(B)	
		B	**S.E.**	**Wald**	**df**	**Sig.**	**Exp(B)**	**Lower**	**Upper**
Step 1[a]	**GENDER(1)**	**6.277**	**2.201**	**8.133**	**1**	**.004***	**532.061**	**7.120**	**39758.599**
	AGE			10.301	5	.067			
	AGE(1)	-.003	2.788	.000	1	.999	.997	.004	235.532
	AGE(2)	-.120	3.005	.002	1	.968	.887	.002	320.690
	AGE(3)	-.136	3.288	.002	1	.967	.873	.001	548.742
	AGE(4)	5.633	3.256	2.993	1	.084	279.452	.473	165013.513
	AGE(5)	.525	3.240	.026	1	.871	1.691	.003	967.984
	MARITAL(1)	-2.968	2.178	1.857	1	.173	.051	.001	3.672
	EDU			**11.629**	**4**	**.020***			
	EDU(1)	**-1.774**	**2.245**	**.624**	**1**	**.002***	**.170**	**.002**	**13.835**
	EDU(2)	.605	2.222	.074	1	.785	1.831	.024	142.671
	EDU(3)	10.073	3.299	9.325	1	.430	23703.760	36.895	15228901.717
	EDU(4)	-.468	2.970	.025	1	.875	.626	.002	211.184
	EMPST			5.165	3	.160			
	EMPST(1)	-4.301	2.333	3.399	1	.065	.014	.000	1.312
	EMPST(2)	-6.961	3.380	4.240	1	.039	.001	.000	.715
	EMPST(3)	.479	3.400	.020	1	.888	1.614	.002	1265.523
	JOBCLASS_2			**8.815**	**3**	**.032***			
	JOBCLASS_2(1)	**-6.282**	**2.213**	**8.057**	**1**	**.005***	**.002**	**.000**	**.143**
	JOBCLASS_2(2)	**-7.608**	**2.832**	**7.219**	**1**	**.007***	**.0005**	**.000**	**.128**
	JOBCLASS_2(3)	-4.605	3.251	2.006	1	.157	.010	.000	5.852
	NUMDPNDT			7.621	4	.106			
	NUMDPNDT(1)	.486	1.862	.068	1	.794	1.625	.042	62.513
	NUMDPNDT(2)	4.233	2.570	2.713	1	.100	68.957	.447	10626.637
	NUMDPNDT(3)	7.310	2.858	6.541	1	.011	1495.235	5.518	405144.817
	NUMDPNDT(4)	6.231	2.477	6.326	1	.012	508.155	3.957	65256.973
	INC			8.748	6	.188			
	INC(1)	3.139	3.020	1.081	1	.299	23.088	.062	8590.280
	INC(2)	7.129	3.214	4.918	1	.027	1247.336	2.290	679370.921
	INC(3)	7.936	3.975	3.986	1	.046	2797.233	1.157	6765451.614
	INC(4)	6.326	3.836	2.719	1	.099	558.709	.303	1029767.973
	INC(5)	5.074	3.858	1.730	1	.188	159.849	.083	307377.713
	INC(6)	5.302	15.375	.119	1	.730	200.661	.000	2454951583744962.000

Continuation of Table 47

	NUMCRD_OVERLCRD			3.354	4	.500			
	NUMCRD_OVERLCRD(1)	-2.621	2.072	1.600	1	.206	.073	.001	4.220
	NUMCRD_OVERLCRD(2)	-3.282	2.142	2.348	1	.125	.038	.001	2.499
	NUMCRD_OVERLCRD(3)	-3.358	2.811	1.428	1	.232	.035	.000	8.589
	NUMCRD_OVERLCRD(4)	1.115	4.368	.065	1	.798	3.051	.001	15933.505
	DEBTtoINCOME			**16.143**	**8**	**.040***			
	DEBTtoINCOME(1)	-4.658	2.779	2.809	1	.094	.009	.000	2.202
	DEBTtoINCOME(2)	7.554	3.861	3.828	1	.050	1907.931	.987	3689557.036
	DEBTtoINCOME(3)	-2.439	2.718	.805	1	.370	.087	.000	17.982
	DEBTtoINCOME(4)	7.687	3.765	3.927	1	.052	1706.822	.768	357988.445
	DEBTtoINCOME(5)	**5.494**	**2.794**	**3.868**	**1**	**.049***	**243.196**	**1.019**	**58052.251**
	DEBTtoINCOME(6)	**5.551**	**2.622**	**4.482**	**1**	**.034***	**257.605**	**1.509**	**43964.482**
	DEBTtoINCOME(7)	**7.469**	**2.968**	**6.331**	**1**	**.012***	**1752.671**	**5.211**	**589504.554**
	DEBTtoINCOME(8)	**14.523**	**4.210**	**11.899**	**1**	**.001***	**2029875.425**	**529.154**	**7786751104.145**
	NREJECT_2			**18.150**	**4**	**.001***			
	NREJECT_2(1)	-.288	2.195	.017	1	.896	.750	.010	55.364
	NREJECT_2(2)	**8.206**	**2.575**	**10.153**	**1**	**.001***	**3664.368**	**23.539**	**570445.732**
	NREJECT_2(3)	**9.759**	**2.610**	**13.977**	**1**	**.000***	**17312.292**	**103.849**	**2886080.102**
	NREJECT_2(4)	**20.845**	**5.363**	**15.106**	**1**	**.000***	**1129831982.890**	**30744.943**	**41519683978254.450**
	NSUCCRD_2			10.525	4	.032			
	NSUCCRD_2(1)	1.221	2.143	.324	1	.569	3.390	.051	226.082
	NSUCCRD_2(2)	-1.786	2.140	.696	1	.404	.168	.003	11.123
	NSUCCRD_2(3)	2.559	2.270	1.271	1	.260	12.920	.151	1104.752
	NSUCCRD_2(4)	-3.498	2.194	2.541	1	.111	.030	.000	2.232
	WEALTH			**15.697**	**4**	**.003***			
	WEALTH(1)	-.941	3.102	.092	1	.762	.390	.001	170.340
	WEALTH(2)	**-11.960**	**4.102**	**8.500**	**1**	**.004***	**.0000064**	**.000**	**.020**
	WEALTH(3)	**-12.166**	**4.394**	**7.665**	**1**	**.006***	**.0000052**	**.000**	**.029**
	WEALTH(4)	3.677	3.837	.918	1	.338	39.522	.021	72904.213
	Constant	-7.933	4.736	2.806	1	.094	.000		
a. Variable(s) entered on step 1: GENDER. AGE. MARITAL. EDU. EMPST. JOBCLASS_2. NUMDPNDT. INC. NUMCRD_OVERLCRD. DEBTtoINCOME. NREJECT_2. NSUCCRD_2. WEALTH.									

* Coefficients significant at $p<0.05$

Table 48 represents overall predictions of the constructed model based on Logistic Regression. Overall prediction of the model was 96.2% indicating that model was able to perform 96.2% accurate predictions of individuals' credit risk. In comparison to beginning classification with 75.6% correct predictions, model performance was considerably enhanced as a result of inclusion of the six independent variables. Percentage of true negatives (event that is not in major scope of interest) and also model specificity was 97.2%. Model accurately predicted 97.2% of individuals at good credit risk status. Sensitivity of the model representing true positives (event of interest / bad credit risk) was 93,1% indicating that 93.1% of individuals having bad credit risk were predicted correctly. Consequently among hypotheses H4a, H4b, H4c, H4d, H4e, H4f, H5a, H5b, H5c, H6a, H6b, H6c, H6d tested by means of this model, H4b, H4d, H4f, H5a, H6b and H6c were accepted.

Table 48
Final Classification Table Model_2

<table>
<tr><th colspan="3" rowspan="3">Observed</th><th colspan="3">Predicted</th></tr>
<tr><th colspan="2">DEBT.Debt behaviour</th><th rowspan="2">Percentage Correct</th></tr>
<tr><th>GOOD</th><th>BAD</th></tr>
<tr><td rowspan="3">Step 1</td><td rowspan="2">DEBT.Debt behaviour</td><td>GOOD</td><td>307</td><td>9</td><td>97.2</td></tr>
<tr><td>BAD</td><td>7</td><td>95</td><td>93.1</td></tr>
<tr><td colspan="2">Overall Percentage</td><td></td><td></td><td>96.2</td></tr>
<tr><td colspan="6">a. The cut value is .500</td></tr>
</table>

5.3.6 Model_3

This conceptual model was based on incorporation of psychometric and financial variables so as to discover each variable’s contribution to explain the debt behaviour. So far, model 1 focused on psychometric variables in order to explain best set of variables discriminating risky behaviour particularly in the case of lack of financial data and past financial behaviour of applicants. Model findings revealed seven significant variables explaining the dependent variable. Model 2 was constructed to assess discriminating power of financial, demographic and socioeconomic variables. As conventional credit scoring decision support systems are based on data from traditional resources, financial knowledge and past behaviour of applicants are still accepted as the major sources of decision making for creditworthiness. Qualitative research in this study also revealed the importance of financial data as it was the priority of decision makers in the case of data availability. However, thin file problem, lack of financial history, growth of young population and opportunities of up-to-date technologies have driven to seek for more agile and comprehensive systems capable of integrating alternative data from different sources.

Major motivation for the proposed decision support system was to integrate a psychometric component to offer more flexible and accurate credit scoring system. Hence, in order to analyse and explore the most powerful set of predictors explaining the dependent variable psychometric and financial variables of model 2 and model 3 were incorporated into a single model (model 3). This model was expected to contribute observing the effect of each predictor when they were all taken into account. Dependent variable and data set was the same as the previous analyses. 425 cases were used in total as shown in the case processing summary (Table 49).

Table 49
Case Processing Summary Model_3

Unweighted Cases[a]		**N**	**Percent**
Selected Cases	Included in Analysis	425	100.0
	Missing Cases	0	.0
	Total	425	100.0
Unselected Cases		0	.0
Total		425	100.0

After incorporating financial, demographic, socioeconomic, situational, personality and value, attitude and behavioural factors, 26 independent variables were remained for the testable LR model. LR procedure with "enter" method initially produced the following classification results which represented prediction results without inclusion of the independent variables. As represented in Table 50, model successfully predicted 74.8% of cases.

Table 50
Beginning Classification Table Model_3

	Observed		**Predicted**		
			DEBT.Debt behaviour		**Percentage Correct**
			GOOD	BAD	
Step 0	DEBT.Debt behaviour	GOOD	318	0	100.0
		BAD	107	0	.0
	Overall Percentage				74.8
a. Constant is included in the model.					
b. The cut value is .500					

According to Omnibus test findings demonstrated in Table 51, model coefficients were statistically significant ($p < 0.05$) which was an indicator of goodness of fit. Statistically significant Chi-square values revealed that independent variables of the model contributed to explain the dependent variable.

Table 51

Omnibus Tests of Model Coefficients Model_3

		Chi-square	df	Sig.
Step 1	Step	387.062	64	.000
	Block	387.062	64	.000
	Model	387.062	64	.000

Overall model fit is represented in Table 52. “Cox & Snell R Square” statistics revealed that 59.8% of change in the dependent variable can be explained by independent variables. According to “Nagelkerke R Square” 88.4% of change in the dependent variable can be explained by independent variables.

Table 52
Model Summary Model_3

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	92.563[a]	.598	.884

Regarding the model fit with sample, “Hosmer and Lemeshow Test” findings revealed insignificant results for Chi-square statistics ($p > 0.05$) indicating good fit between model and the sample utilized.

Table 53
Hosmer and Lemeshow Test Model_3

Step	Chi-square	df	Sig.
1	1.168	8	.997

Based on the prediction results variables having significant effect on the dependent variable are demonstrated in Table 54. Among financial, socioeconomic and demographic variables, four variables contributed to the explanation of debt behaviour. These variables included employment status (EMPST), number of previously rejected credits (NREJECT_2), number of successfully repaid credits (NSUCCESS_2) and wealth (WEALTH). Categories of employment status was defined as follows: (1) Employed (regular full time), (2) Self-employed, (3) Retired, (4) Unemployed. Compared to being employed, being self-employed increased the probability of being in bad credit status by 2.8 times. Compared to being employed, being a retired person increased the probability of being in good credit status group. But, this was a very small effect as observed Exp (β) value was 0.0002.

Number of rejected credits was another significant financial indicator ($p < 0.01$). Participants reported that they had one rejected credit application were more likely to be in bad credit risk group compared to those who reported that they did not apply for credit before. Risk for this group was almost 38.6 times higher. When the number of rejected credits increased, the probability of bad credit risk increased as well. Participants reported 2-3 rejected credit applications, odds of bad credit risk was higher. Probability of being in the risky credit group was 142.7 times increased. For participants reported more than 4 rejected credit applications risk was remarkably higher indicating the significance of this variable. Compared to those who did not apply for credit before, having more than 4 rejected credit applications increased the probability of bad credit risk by 194.1 times.

In contrast to financial model (model 2), number of successfully repaid credits was also explored as a significant predictor ($p < 0.01$). Participants reported that they had one successfully repaid credit application were more likely to be in good credit risk group compared to those who reported that they did not apply for credit before. The probability of belonging to good credit status group was 0.012 times increased for this group. Also, participants who reported more than 4 successfully repaid credits were more likely (0.017 times) to be in good credit status group compared to those did not apply before.

Wealth of applicants was again found a significant indicator of dependent variable ($p < 0.05$). Reporting bad wealth status decreased the credit risk compared to respondents who perceived their wealth status very bad. For change in the wealth status from bad to very bad 10.942 unit decrease was expected in the log odds of the dependent variable (β coefficient represents the change in log odds comparing moderate to very bad wealth status group). Also, participants stated that their wealth status was bad were more likely to be in good credit risk group compared to respondents who perceived their wealth status very bad. Similarly, for change in the wealth status from moderate to very bad 12.411 unit decrease was expected in the log odds of the dependent variable (B coefficient represents the change in log odds comparing good to very bad wealth status group). Exp (β) values or odds ratios less than 1 presented low level of risk decrease for the studied group compared to reference group. Exp (β) values less than .00005 indicated that reporting bad or moderate wealth status very slightly increased the probability of being in the good credit risk group compared to participants perceived their wealth status very bad.

As in the psychometric model (model 1), situational variables or experience of adverse life events had significant contribution in discriminating individuals based on creditworthiness. ST is a dummy variable representing experience of adverse life events (ST=1 for positive responses; ST=0 for negative responses). In this case, reference category was set as the group did not experience adverse life events, and Exp (β) of situational factors (ST) demonstrates the percentage of odds ratio in the case of presence of situational factors compared to reference category (ST=0 for negative responses). Hence, bad credit risk was 52.8 times more likely to occur in the case of experience of adverse life events. Situational factors, therefore had considerable impact on discriminating individuals with bad credit risk.

Except from situational variables, seven psychometric variables were found significant correlates of dependent variable. Positive B coefficients indicated increase in the probability of credit risk as the original coefficients were represented in terms of logit values. In contrast, negative B coefficients represented decrease in credit risk. When results were examined, it was observed that 7 variables including social sanctions, risky credit behaviour, conscientiousness, attitudes towards money_retention, neuroticism, social motivation and financial management were statistically significant. In contrast to model 1, considering mix of variables revealed different results for psychometric variables. For instance, social sanctions and attitudes towards money_retention were discovered as significant predictors of the dependent variable. Contrarily, risk aversion which was found as a significant determinant for model 1, did not contribute to the explanation of the dependent variable for this model. Hence, when the impact of financial, demographic and socioeconomic variables were considered mix of psychometric variables included in the model changed.

Among factors causing increase in good credit score, one-unit increase in social sanctions score almost 0.38 times increases the probability of being in good credit status group. Conscientiousness had relatively similar magnitude of influence with Exp (β) value of 0.22. One-unit increase in conscientiousness score, 0.22 times increase the probability of being in good credit status group. Regarding the risky credit behaviour, it was discovered that this factor increased the credit risk almost 7.24 times constituting a considerable antecedent of problematic loan behaviour.

Having retention attitude towards money and financial management factors also contributed to increase the probability of having good credit score with Exp (β) values of 0.23 and 0.24. Factors almost had the same magnitude of influence with one-unit increase in the score of these factors multiplied the probability of belonging to good credit status group by 0.23 and 0.24. Social motivation had remarkable impact on increasing bad credit risk as one-unit increase in social motivation rises the risk 16.9 times. Another factor contributing to increase of credit risk was neuroticism. Increase in neuroticism score multiplies the probability of belonging to bad credit risk group by 2.94.

Table 54
Variables in the Equation Model_3

		B	S.E.	Wald	df	Sig.	Exp(B)	95% C.I.for EXP(B)	
								Lower	Upper
Step 1[a]	GENDER(1)	1.812	1.279	2.007	1	.157	6.124	.499	75.128
	AGE			9.679	5	.085			
	AGE(1)	4.827	3.046	2.512	1	.113	124.855	.319	48847.348
	AGE(2)	8.115	3.272	6.151	1	.013	3345.814	5.486	2040658.179
	AGE(3)	7.561	3.304	5.235	1	.022	1921.257	2.957	1248340.174
	AGE(4)	10.308	3.528	8.538	1	.003	29963.725	29.772	30156994.342
	AGE(5)	9.792	3.527	7.706	1	.006	17881.470	17.783	17980301.241
	MARITAL(1)	-.567	2.013	.079	1	.778	.567	.011	29.307
	EDU			7.089	4	.131			
	EDU(1)	4.415	2.478	3.174	1	.075	82.665	.643	10631.416
	EDU(2)	1.947	2.157	.815	1	.367	7.005	.102	479.961
	EDU(3)	-3.541	1.337	7.012	1	.660	.029	.002	.398
	EDU(4)	.777	3.155	.061	1	.805	2.175	.004	1053.418
	EMPST			**12.398**	**3**	**.006***			
	EMPST(1)	**1.012**	**2.300**	**.194**	**1**	**.008***	**2.752***	**.030**	**249.631**
	EMPST(2)	**-8.493**	**3.230**	**6.914**	**1**	**.009***	**.00021***	**.000**	**.115**
	EMPST(3)	2.936	2.746	1.143	1	.285	18.835	.087	4094.292
	JOBCLASS_2			3.309	3	.346			
	JOBCLASS_2(1)	-2.084	1.202	3.005	1	.083	.124	.012	1.313
	JOBCLASS_2(2)	-2.235	2.879	.602	1	.438	.107	.000	30.227
	JOBCLASS_2(3)	-1.477	2.707	.298	1	.585	.228	.001	46.041
	NUMDPNDT			9.205	4	.056			
	NUMDPNDT(1)	-3.147	2.022	2.422	1	.120	.043	.001	2.263
	NUMDPNDT(2)	1.604	1.836	.764	1	.382	4.973	.136	181.558
	NUMDPNDT(3)	-.850	1.738	.239	1	.625	.428	.014	12.902
	NUMDPNDT(4)	3.464	1.989	3.033	1	.082	31.953	.648	1576.528
	INC			6.655	6	.354			
	INC(1)	4.525	2.774	2.661	1	.103	92.283	.402	21194.267
	INC(2)	5.976	3.070	3.788	1	.052	393.831	.959	161751.876
	INC(3)	2.933	3.038	.933	1	.334	18.789	.049	7235.110
	INC(4)	7.147	3.864	3.421	1	.064	1269.685	.653	2470576.885
	INC(5)	5.560	3.867	2.067	1	.150	259.815	.133	508467.901
	INC(6)	4.920	5.865	.704	1	.401	137.036	.001	13452994.817
	NUMCRD_OVERLCRD			4.560	4	.336			
	NUMCRD_OVERLCRD(1)	-1.864	1.462	1.626	1	.202	.155	.009	2.722

Continuation of Table 54

NUMCRD_OVERLCRD(2)	-3.210	1.858	2.984	1	.084	.040	.001	1.540
NUMCRD_OVERLCRD(3)	-1.068	1.948	.301	1	.583	.344	.008	15.647
NUMCRD_OVERLCRD(4)	2.560	4.313	.352	1	.553	12.938	.003	60676.365
DEBTtoINCOME			14.441	8	.071			
DEBTtoINCOME(1)	-3.617	2.007	3.248	1	.072	.027	.001	1.373
DEBTtoINCOME(2)	-5.850	2.532	5.337	1	.021	.003	.000	.412
DEBTtoINCOME(3)	-2.059	2.554	.649	1	.420	.128	.001	19.068
DEBTtoINCOME(4)	3.184	1.695	3.527	1	.060	24.139	.870	669.620
DEBTtoINCOME(5)	2.633	2.457	1.148	1	.284	13.909	.113	1716.158
DEBTtoINCOME(6)	2.072	2.250	.848	1	.357	7.938	.097	652.636
DEBTtoINCOME(7)	.223	1.927	.013	1	.908	1.250	.029	54.588
DEBTtoINCOME(8)	1.765	1.800	.962	1	.327	5.841	.172	198.821
NREJECT_2			**16.549**	**4**	**.002***			
NREJECT_2(1)	-.275	1.730	.025	1	.873	.759	.026	22.520
NREJECT_2(2)	**3.653**	**1.900**	**3.695**	**1**	**.055***	**38.582**	**.931**	**1598.817**
NREJECT_2(3)	**4.961**	**2.062**	**5.785**	**1**	**.016***	**142.684**	**2.505**	**8127.127**
NREJECT_2(4)	**5.268**	**2.361**	**4.981**	**1**	**.026***	**194.094**	**1.899**	**19833.261**
NSUCCRD_2			**14.837**	**4**	**.005***			
NSUCCRD_2(1)	1.581	2.456	.415	1	.520	4.862	.039	599.103
NSUCCRD_2(2)	**-4.434**	**2.125**	**4.353**	**1**	**.037***	**.012**	**.000**	**.764**
NSUCCRD_2(3)	.454	1.808	.063	1	.802	1.575	.046	54.438
NSUCCRD_2(4)	**-4.092**	**2.021**	**4.098**	**1**	**.043***	**.017**	**.000**	**.878**
WEALTH			**11.266**	**4**	**.024***			
WEALTH(1)	**-10.942**	**4.999**	**4.792**	**1**	**.029***	**.000018**	**.000**	**.318**
WEALTH(2)	**-12.411**	**5.018**	**6.116**	**1**	**.013***	**.000004**	**.000**	**.076**
WEALTH(3)	-8.777	4.847	3.280	1	.070	.000	.000	2.059
WEALTH(4)	-4.980	6.795	.537	1	.464	.007	.000	4183.164
ST(1)	**3.966**	**1.128**	**12.358**	**1**	**.000***	**52.762**	**5.782**	**481.477**
Social Sanctions	**-1.087**	**.473**	**5.277**	**1**	**.022***	**.337**	**.133**	**.852**
Risky Credit Behaviour	**1.979**	**.736**	**7.229**	**1**	**.007***	**7.235**	**1.710**	**30.619**
Conscientiousness	**-1.507**	**.588**	**6.572**	**1**	**.010***	**.222**	**.070**	**.701**
Spending Behaviour	.834	.589	2.008	1	.156	2.304	.726	7.305
Attitudes towards Money (Power & Prestige)	-.115	.385	.090	1	.764	.891	.419	1.896
Extraversion / Introversion	-.556	.468	1.415	1	.234	.573	.229	1.434
Attitudes towards Money (Retention)	**-1.481**	**.471**	**9.887**	**1**	**.002***	**.227**	**.090**	**.572**
Neuroticism	**1.077**	**.489**	**4.849**	**1**	**.028***	**2.937**	**1.126**	**7.660**
Social Motivation	**2.827**	**.762**	**13.781**	**1**	**.000***	**16.895**	**3.798**	**75.159**
Financial Management	**-1.436**	**.540**	**7.067**	**1**	**.008***	**.238**	**.083**	**.686**
Self -control	-.811	.527	2.373	1	.123	.444	.158	1.247
Risk Aversion	.856	.470	3.322	1	.068	2.355	.937	5.915
Constant	-6.017	5.634	1.141	1	.286	.002		
a. Variable(s) entered on step 1: GENDER, AGE, MARITAL, EDU, EMPST, JOBCLASS_2, NUMDPNDT, INC, NUMCRD_OVERLCRD, DEBTtoINCOME, NREJECT_2, NSUCCRD_2, WEALTH, ST, FAC1_2, FAC2_2, FAC3_2, FAC4_2, FAC5_2, FAC6_2, FAC7_2, FAC8_2, FAC9_2, FAC10_2, FAC11_2, FAC12_2.								

* Coefficients significant at p<0.05

Considering the predictors having significant contribution, Table 55 demonstrates the overall prediction results for model 3. Overall prediction of the model was 95.8% which signifies that model was able to classify 95.85% of cases accurately. In comparison to beginning classification with 74.8% correct predictions, model performance was considerably enhanced as a result of inclusion of the twelve independent variables.

Percentage of true negatives (event that is not in major scope of interest) and also model specificity was 97.5%. Model accurately predicted 97.5% of individuals at good credit risk status. Sensitivity of the model representing true positives (event of interest / bad credit risk) was 90.7% indicating that 90.7% of individuals having bad credit risk were predicted correctly. Model 3 tested all of the hypotheses developed for the study and as a result H1b, H1c, H2c, H2d, H2e, H2f, H2h and H3, H4c, H6c and H6d were accepted.

Table 55
Final Classification Table Model_3

	Observed		**Predicted**		
			DEBT.Debt behaviour		**Percentage Correct**
			GOOD	BAD	
Step 1	DEBT.Debt behaviour	GOOD	310	8	97.5
		BAD	10	97	90.7
	Overall Percentage				95.8
a. The cut value is .500					

5.4 Discussions

In this study, three models for risk assessment in credit lending were proposed. This is the basic version of a decision support model integrating two main components. Model 1 is the psychometric model that predicts default probability based on Logistic Regression. Dataset was divided into two subsets and variables having significant impact on categorizing the applicants into two main risk groups (good / bad) were identified. This component can be incorporated into main credit risk models in the case of data scarcity or can be implemented as a secondary screening mechanism for making more accurate predictions. This model and the estimated coefficients is capable of quantifying credit risk of new applicants depending on its default probability.

Model 1 investigated the predictive ability of psychological factors gathered from qualitative findings. Among thirteen variables tested, seven variables contributed to distinguish individuals' debt behaviour. This predictive model transformed predictor variables including adverse life events, risky credit behaviour, conscientiousness, neuroticism, social motivation, financial management and risk aversion into the default probability. Psychometric variables contributing to build credit risk models have attracted remarkable attention from academic studies and practical implementations. The set of factors having predictive ability have substantially changed across countries and samples drawn. Practical implementations in this area have originated from Western cultures and exploration of country specific indicators is an important research gap. As the empirical results revealed, compared to previous literature some contradictory results were achieved. This study have contributed to the literature by revealing a country specific model with psychometric attributes.

In general, findings confirm the hypotheses postulating that experience of adverse life events has significant impact on debt behaviour of individuals. As expected and confirmed in previous studies (Chakravarty and Rhee, 1999: 10; Costa, 2012; Avery et al., 2004; Rogers et al., 2015) situational factors considerably increased the chance of having debt and repayment problems. Situational factors emerged as the most powerful indicator of debt behaviour because the probability of belonging to risky group almost increases by 22 times in the case of experiencing adverse life events. Triangulation with the systematic review and focus group study, situational factors were explored as an important indicator of creditworthiness in this study.

Predictors including risky credit behaviour and social motivation had significant contribution to distinguish individuals having risky debt behaviour as risk was almost increased 3 times with one-unit increase in risky credit behaviour score and 2 times with one-unit increase in social motivation score. Examining in detail risky credit behaviour, literature has consistently revealed that risky credit / credit card behaviour is closely linked with future financial problems (Robb, 2011; Kennedy, 2013; Jiang et al., 2018; Norvilitis and MacLean, 2010; Šušteršič et al., 2009). Regarding the social motivation, results confirmed the hypothesis that social motivation has significant impact on debt behaviour. Social motivation had remarkable impact on increasing credit risk as one-unit increase in social motivation rises the risk approximately 2 times. Social motivation / subjective norms refers to individual’s beliefs and perceptions with regard to others approval for a particular behaviour. Stated in other words it is one’s degree of getting other people’s assistance and advice for performing a certain behaviour and his/her inclination to pay attention to that behaviour (Limbu, 2017: 845-846). If one have positive attitudes towards debt repayment and have support from others (family, friends etc.), and if him / her own repayment capability as well, than it is expected that repayment behaviour will take place (Ismail, 2011). Limbu (2017) explored that social motivation was negatively and significantly associated with credit misuse. However, in contrast to empirical evidence regarding the negative impact of social motivation on credit risk, positive impact was observed in this study. One possible explanation for this positive impact on credit risk might be participants' tendency of agreeing to commonly accepted beliefs and behaviours. Being a collectivist culture, in Turkey others beliefs and perceptions take important place in individuals' life and inclination for paying attention to those beliefs is widely accepted as a decent behaviour. Hence, social desirability might have caused this outcome.

Based on qualitative findings, among Big Five traits, conscientiousness, neuroticism and extraversion were included for quantitative assessment. In contrast to previous findings, findings of this research was not in agreement regarding the influence of extraversion on debt behaviour. Extraversion was not found a significant indicator of debt behaviour. However, higher level of conscientiousness which was confirmed by the prior studies as well (Davey and George, 2011; Brown and Taylor 2014; Gagarina and Shantseva, 2017) decreased the probability of default. Examining in detail, findings of the literature associated with the influence of neuroticism on debt behaviour were mixed. Some studies did not explore a significant influence (Harrison and Chudry, 2011), whereas some researchers found that neuroticism / emotional instability were closely linked with indebtedness or irresponsible financial behaviour (Bivens et al., 2013; Addad and Leslau, 1990; Nyhus and Webley, 2001; Davey and George, 2011; Donnelly et al., 2012; Zainol, 2016; Ganzach and Amar, 2017). This study was in agreement with previous studies explored significant impact. Increase in neuroticism approximately 2 times increased the chance of being in risky group. Conscientiousness was not as powerful as neuroticism in distinguishing groups, as increase in conscientiousness reduced the probability of belonging to bad credit group by 0.6 times.

Financial management and risk aversion had similar magnitudes of influence on the outcome variable and demonstrated negative effect on credit risk. Level of debt was considered as consequence of negative financial behaviour by the relevant literature (Xiao, 2008). Findings supported the previous studies that confirmed poor financial management was an antecedent of over-indebtedness (D'Alessio and Lezzi, 2013; Hoeve et al., 2014). Credit risk decreased 0.4 times by one-unit increase in financial management score reflecting responsible financial behaviour and decision making with taking into account its consequences decreases default risk of individuals. Similarly, risk aversion decreases probability of exhibiting bad debt behaviour almost 0.7 times. In support of this study's finding, previously L. Wang, Lv, et al. (2011) explored that attitudes towards risk significantly predicted credit misuse. Also, some other research explored significant effect for risk aversion (Brown et al., 2013; Tokunaga, 1993; Borghans et al., 2008; Sidoti and Devasagayam, 2010).

Depending on the discussions above, a particular picture for profiling of individuals that have the highest risk propensity in terms of credit repayment was achieved. Mix of psychometric variables revealed can be anticipated as potential country specific indicators of creditworthiness. In contrast to previous literature, predictors including social sanctions, spending behaviour, attitudes towards money, extraversion and self-control were not explored as significant influencers of debt behaviour. Prediction accuracy of the psychometric model was 86.2% and using the psychometric indicators, model that was constructed predicted 86.2% of cases correctly. This model can be combined into conventional credit scoring systems for improving prediction accuracy or can be used as a secondary screening mechanism. In the case of data scarcity or situations where instant decision making is needed with limited applicant information such as online lending, psychometric tests can be applied for assessing applicants.

Conventional models mostly depend on socioeconomic, demographic and financial indicators and model 2 was constructed and tested for discovering the optimum mix of parameters for classifying individuals. Model constructed by these parameters achieved a prediction accuracy of 96.2% that is greater than the prediction accuracy of psychometric model. This is not a surprising result as the traditional approach confirms the significance of financial indicators and payment history in giving credit granting decisions. Derived weights as a consequence of AHP implementation also allocated more level of importance for this group of indicators (members indicated that this set of parameters (70.90%) was more important than psychometric parameters (29.10%)).

This model (model 2) used gender, education, occupational class, debt-to-income ratio, number of previously rejected credits and perceived wealth status for quantifying probability of default. Findings of this analysis demonstrated mixed results as some variables were unexpectedly found insignificant. For instance, in contrast to previous studies mostly explored significant effect for age, marital status, employment status, number of dependents, income, number of credit cards that exceeded spending limit and number of successfully repaid credits, this study did not explore significant influence for those factors.

However, focus group study allocated relatively lower degree of importance for those factors. Especially, demographic factors including age, gender and marital status; socioeconomic factors including number of dependents, income, education and occupation were not found as important as debt-to-income ratio, status of previous credits (unpaid) and number of declined credits. On the other hand, credit card use patterns or number of credit cards that exceeded the spending limit which were attained comparatively higher level of importance by the participants were not explored to have significant influence on debt behaviour in quantitative analysis. In contrast to some mixed results, findings are compatible with the focus group outcomes to a great extent. Exp (β) coefficient of gender variable demonstrates the percentage of odds ratio in the case of being female compared to reference category. Thus, credit risk was almost 532 times more likely to occur in female group compared to male group. Gender, therefore had remarkable impact on discriminating individuals with high level of risk.

Education was another significant indicator ($p < 0.05$) and primary school graduates were defined as the reference category. The only significant effect was observed for secondary school graduates, and compared to primary school graduates belonging to this category decreases credit risk almost 0.2 times. This was an interesting finding as no significant differences were observed when the level of education increased. However, contribution of the variable to the model was not too much and results necessitated further investigation. 40% of primary school graduates were employers and employees working for a regular full time job was mostly formed (46%) of the secondary school graduates. At the same time, occupational class was found as a significant influencer as compared to being an employer, credit risk 0,002 times decreased in the case of being an employee and 0.0005 times decreased for employees at management level. Therefore, probability of high risk of primary school graduates can be attributed to high number of employers among this group. Although demonstrating weaker estimation, education and occupational class (JOBCLASS_2) made contribution to the explanation of the debt behaviour.

Another predictor exhibiting limited prediction was perceived wealth status. Exp (β) values less than .00005 indicated that reporting good or moderate wealth status very slightly increased the probability of being in the good credit status compared to participants perceived their wealth status very bad. Nevertheless, this variable significantly contributed to the model.

Contribution of debt-to-income ratio and number of previously rejected credits to the model prediction was high and discriminating power of these variables were strong. Participants reported that their overall debt was almost 5 times of their monthly income had greater odds and bad credit risk was almost 258 times higher for this group. In the case of participants who reported overall debt more than 5 times of their monthly income and more than 10 times of their monthly income, odds ratios were far greater. Particularly, those who reported overall debt more than 10 times of their monthly income were constituted the individuals with highest credit risk. In the case of participants reported 2-3 rejected credit applications, odds of bad credit risk was higher. For participants who reported that they had 4 rejected credit applications, β coefficient was extremely high indicating that this group of individuals carries the highest risk in terms of loan behaviour. This finding definitely supports the qualitative findings attained the highest level of importance to these two indicators. Additionally, among this group of parameters, financial / payment history factors (60.50%) was weighted more heavily than the socioeconomic (31.20%) and demographic (8.30%) factors according to AHP results. Overall predictive performance of the model 96.2% exhibited better performance than the psychometric model and heavily depending on financial indicators a predictive model with good discriminating power was established.

As aforementioned earlier, socioeconomic, demographic, financial and psychometric indicators were incorporated into a single model for observing the overall performance and exploring discriminating power of variables when taken into account together. Model achieved 95.8% discriminating power which was slightly less than the financial model, but greater than the psychometric model. However, mix of variables contributed to the model specification was different and unexpected.

Among financial, socioeconomic and demographic variables four variables contributed to the explanation of debt (loan) behaviour. These variables included employment status, number of previously rejected credits, number of successfully repaid credits and wealth. Instead of occupational class revealed significant effect in model 2, employment status was found as a significant influencer. However, findings regarding the increasing risk in employer group again observed for different categories of employment status. Compared to being employed, being self-employed increased the probability of being in good credit status group by 0.029 times and compared to being employed, being a retired person also increased the probability of being in good credit status group.

Number of rejected credits was again another significant financial indicator ($p < 0.01$). As the number of rejected credits increased the probability of being in bad risk status increased as well. Nevertheless, the magnitude of the impact was not as big as observed for the financial model (model 2). However, this was still a powerful indicator as for participants reported 2-3 rejected credit applications, probability of being in the risky credit group increased 142.7 times. For participants reported more than 4 rejected credit applications risk was remarkably higher. Compared to those who did not apply for credit before, having more than 4 rejected credit applications increased the probability of bad credit risk by 194.1 times. Together with number of rejected credits, number of successful repayments was also contributed to the model. Although, this was not explored as an indicator of credit risk in the previous analysis, this finding was consistent with the previous literature and qualitative study outcomes. As the number of successfully repaid credits increase, the probability of being in good credit status increases as well. Also, participants who reported more than 4 successfully repaid credits were more likely (0.017 times) to be in good credit status group compared to those did not apply before and the probability of belonging to good credit status group was 0.012 times increased for the respondents reported one successful repayment. None of the demographic variables had contribution to the explanation of the dependent variable. Wealth was again a significant indicator, but with a weak magnitude of effect. For this set of indicator, solely number of rejected credits demonstrated strong influence on the explanation of the model. However, the aforementioned variables were found as significant influencers, and they contributed to distinguish individuals based on their risk level.

Among psychometric variables most of them explored as significant influencers. In contrast to model 1, considering mix of variables revealed different results for psychometric variables. For instance, social sanctions and attitudes towards money_retention were discovered as significant predictors of the dependent variable. Contrarily, risk aversion which was found as a significant determinant for model 1, did not contribute to the explanation of the dependent variable for this model. These results indicates that taking all group of predictors into account causes different outcomes. Hence, in the case of integration of a psychometric model into the credit scoring model implementation of a different model is required.

Regarding the risky credit behaviour, it was discovered that this factor increased the credit risk almost 7.24 times constituting a considerable antecedent of debt behaviour. Social motivation had remarkable impact on increasing bad credit risk as one-unit increase in social motivation rises the risk 16.9 times. Another factor contributing to increase of bad credit risk was neuroticism. Increase in neuroticism score multiplies the probability of belonging to bad credit risk group by 2.94. Another powerful indicator was experience of adverse life events. As in the psychometric model (model 1), situational variables or experience of adverse life events had significant contribution in discriminating individuals based on creditworthiness. Credit risk was 52.8 times more likely to occur in the case of experience of adverse life events. Situational factors, therefore had considerable impact on discriminating individuals with bad credit risk.

Having retention attitude towards money and financial management factors also contributed to increase the probability of having good credit status. Factors almost had the same magnitude of influence with one-unit increase in the score of these factors multiplied the probability of exhibiting good credit status by 0.23 and 0.24.

In the research data, strong influence of risky credit behaviour was noticed. In addition, financial management assessing responsible financial behaviour was a significant indicator. These variables are related with information involving financial practices, credit, savings, planning and money management. Financial behaviour which is generally assessed through financial ratios was measured by means of a scale evaluating subjective perceptions of the participants regarding their own financial management behaviour and risky credit behaviour. Hence, these two constructs were included under the psychometric model. However, in practical, these variables that were evaluated under psychometric variables do not necessarily need to be evaluated in same manner. In practical, financial ratios can be integrated into credit scoring models. However, contribution of these variables are important and in the case of building a psychometric scoring model when information regarding the financial ratios of applicant is limited these behavioural information can be assessed through psychometric tests.

CONLUSIONS & RECOMMENDATIONS

Summary of Research

However, while unconsciously spending and inappropriate credit usage cause problems on an individual basis, it causes losses for banks and financial institutions, as a result of granting credits without proper risk assessments and analysis. Consequently, lending decisions have become very important for banks and financial institutions. The decision making process is a complex process that requires considerable experience associated with the decision problem and takes into account many factors. Subjective evaluations of decision makers in credit decision processes can increase credit portfolio risk, which might lead to various losses.

When the associated literature is examined, different types of decision support systems that were developed to support credit decision processes have been explored. Each of these systems employs different techniques and parameters according to the areas and contexts in which they are used. In this context, decision support systems implement credit scoring models to reduce the risks and increase profitability by enabling decision makers to make risk assessment by using different techniques and indicators.

In developing countries, a large portion of the population has problems in terms of access to credit due to lack of registered credit history and third parties such credit bureaus, which gather information from different sources. Therefore, contemporary trend for those countries is to improve the credit evaluation mechanisms by using various alternative methods and to increase the accessibility of each segment by managing the risks properly.

The economic crises experienced by the banks and the financial sector and the strong competition in the field have made credit scoring more important. Consistent and accurate estimations in the calculation of credit risk is possible with decision support systems that assist decision makers in this highly competitive environment. Many classification and estimation methods have been used in the literature. Each of these methods gathers different parameters from various sources and processes them in an integrated way with different algorithms, and makes credit evaluation for customers or institutions. Although many banks use one of the existing developed credit scoring models, it is an important problem to decide which model to use and choose for implementing the right system.

Different credit types and different industries require different credit scoring models and they integrate their models with credit bureau data to determine the credit risk level of customers. Some specialised credit scoring mechanisms basically integrate psychometric properties of applicants, however these mechanisms stemming from developed countries are not applicable in other cultures and contexts. The literature review reveals that the new and current techniques have great potential in improving the performance of credit evaluation. For instance, there are studies on using social media data and data from different sources such as psychometric evaluation in credit risk assessment.

Individuals may need loans for many different purposes and there are many different types of loans. Micro-loans are small amounts of loans that can be provided by individuals, credit cooperatives or different investors. The goal is to offer loan to individuals who cannot reach loans under the strict rules of the banks. Providing small-scale financial support, especially for those with low income and no proof of credit history, is seen as a profitable niche market. However, this business model necessitates flexible and fast decision making mechanisms.

As a result of the researches conducted, it was determined that there was no technological solution that would support the lending to provide instant credit decisions in Turkey. Currently, conventional systems with some financial data have been in use in finance sector. There were deficiencies in the existing systems and risk estimation for a remarkable number of people cannot be performed due to lack of financial history. Hence, this dissertation aims to propose a system model that considers data from different channels and analyses them with decision models to be developed and offers suggestions and risk levels for credit approval / rejection decisions.

Hence, such a system, which is based on credit scoring module, needs to integrate different data from different sources. The decision support system, which is aimed for Turkey, is quite different from the conventional business models of banks and requires a different model for calculating the relevant score in this context. Lenders have to make this decision quickly with limited data and documents from the customers, so the system must be able to cope with this kind of data constraints and integrate alternative sources. In this context, determining credit risk models to be used and parameters supporting the decision making contribute to meet this requirement. Consequently, objectives of this dissertation are as follows;

- Identifying modules supporting the credit decision flow within the limits of the system (financial and psychometric modules)
- Determining parameters that the system takes into account for credit risk assessment
- Determining parameters having the most powerful impact on risk estimation by refining these parameters with qualitative and quantitative methods
- Designing and validating credit risk models producing quantitative risk estimates and testing the proposed theoretical models by means of the data set
- Integration of the most appropriate models to ensure consistent and realistic risk assessment

Summary of Findings

Research methodology of this dissertation adopted mixed methods. Qualitative methods were used predominantly for the determination of the indicators for construction of the conceptual models. Through these methods, such as interviews and focus group, it was aimed to explore the problems and requirements related to the field in detail and capture context specific indicators of creditworthiness. Hence, in order to integrate different facets of creditworthiness into credit risk model, Analytic Hierarchy Process was performed for defining weights for factor groups. Systematic review process implementing content analysis was conducted to double check and synthesize the findings of focus group study and semi structured interviews. Hypotheses and conceptual models constructed were tested by means of applying Logistic Regression analysis. For testing the models, data was collected by means of a well-structured questionnaire and face-to-face administration method. Convenience sampling technique was used to choose participants of the study. Having a response rate of 82%, 425 usable questionnaires were achieved. Hence, ultimate sample size of the study was 425. Research procedure implemented the followings steps:

- Detailed literature review
- Project discussions & workshops

- Focus group study
- Analysis of findings + semi-structured interviews
- Pilot study design & implementation (preliminary study for psychometric model)
- Analysis of findings + Systematic review
- Conceptual model & development of hypotheses
- Survey design & implementation
- Quantitative data analysis
- Findings & conclusions

Summary of Qualitative Findings

Within the scope of the focus group study following steps of research process were completed:

- New ideas, parameter suggestions, approaches and evaluations from the team of academicians, practitioners and industry experts were captured.
- Determination of the importance of these parameters in the credit risk assessment by sharing the literature findings was provided.
- Literature findings related with parameters were categorized under particular main-parameter groups including financial / payment history, socioeconomic, demographic, personality, value / attitude and behaviour and situational factors.
- Importance of new parameters were graded by other participants during the study.
- Weights of the resulting main-parameter groups were defined by Analytic Hierarchy Process.

Among the financial / payment history factors most of them found important. Participants indicated that "presence of bankruptcy status declared in the previous year" is extremely important in assessment of credit risk. Participants also allocated high level of importance to factors associated with credit history, credit card debt to limit ratio, status of previous credits, number of delinquent times, debt-to-income ratio, relationship with bank, number of credit cards, credit card use patterns and length of credit history.

Participants did not give very high level of importance to socioeconomic indicators compared to financial predictors. Income and disposable personal income were found more important than the other indicators. Nevertheless, most factors were found at least moderately significant by the group members.

Demographical factors were often traditionally integrated to credit risk models. Highest degree of importance was given to family life cycle stage of individuals. In parallel with this criterion, age was also considered as an important indicator by the members. Importance level of gender and marital status were reported moderate.

Regarding the personality factors, conscientiousness was found as the strongest predictors of Neuroticism / emotional stability and agreeableness were also rated as important influencers. In the case of value, attitude and behaviour factors compared to other group of parameters the extent of importance attained to this set of predictors were higher in general. Except from social comparisons and collectivist culture, all factors were found considerably important by the participants. These factors included risk aversion, compulsive buying, money attitudes, time horizon, decision making style, locus of control, financial literacy and social sanctions.

Regarding the situational variables, list of adverse life events were presented to participants. Importance attained to marital separation, medical expenses, imprisonment and loss of job were higher than the other negative life events. Data from alternative sources have been heavily investigated, and incorporated into risk models currently. Alternative factors except from psychometric data gained less level of importance compared to other set of predictors.

Not all the group of parameters would have the same importance. Hence, last session of the focus group study was designated for AHP implementation process in order to determine intensity of importance of main-group parameters. Results for AHP are as follows:

- Weight of Financial Factors=70.90%
- Financial / Payment History Factors=60.50% (overall weight=42.89%)
- Socioeconomic Factors=31.20% (overall weight=22.12%)
- Demographic Factors=8.30% (overall weight=5.88%)
- Weight of Psychometric Factors=29.1%
- Personality Factors=34.70% (overall weight=10.10%)

- Value, Attitude and Behaviour Factors=27.30% (overall weight=7.94%)
- Situational Factors=38.00% (overall weight=11.06%)

Findings represented that experts prefer financial information to psychometric information. However, psychometric parameters were remarkably important for participants and findings of this assessment was kept for further investigation and model construction phase.

Some of the predictors that were mentioned by focus group members, especially new suggested parameters, indicated similar concepts and had the same meanings although the terminology was different. Hence, semi-structured interviews were performed for refining the parameter set again for mapping the similar concepts indicating the same phenomenon. Findings for semi-structured interviews are as follows:

The interviewees' responses regarding the existing list of variables did not contradict. Most participants agreed with the importance of the variables. At another step, focus group findings and the ratings for the level of importance were presented to participants. Sensation seeking was proposed for elimination by the participants as it was a facet of Big Five traits.

Interviewees agreed with the complexity of some concepts and reported that Big Five personality measure was sophisticated enough to include certain facets of personality. Accordingly, in order to prevent redundancy of personality indicators Big Five personality inventory was offered by the participants for inclusion in the final model. However, regarding the importance of these five dimensions there were mixed comments about their relevance with the outcome that the study aims to assess.

Social comparisons, which was also found relatively less important was suggested for exclusion by the interviewees. Among situational factors, contrast to focus group participants, interviewees attained higher priority to the event of "death of a close family member" and suggested for inclusion among situational factors. Events that were discovered contextually inappropriate were proposed for exclusion. As a result, situational factors incorporated nine life events.

Some participants announced that the concept of "collectivist culture" was probably misunderstood, as its meaning presented to focus group participants more put emphasis on social motivation and subjective norms. It was reported that norms in collectivist cultures were more influential in attitudes and behaviour of individuals.

Regarding the “compulsive buying”, some interviewees indicated that compulsive buying was a consequence of a self-control problem, and making inappropriate and purposeless decisions were closely related with lack of self-control.

Some participants reported that openness to experience as it was discovered less important in the focus group study might be excluded from the conceptual model. Although focus group participants rated the agreeableness characteristic as important, interviewees criticised that and suggested for exclusion. Based on comments of some interviewees, conceptual relationship of risk preferences (risk aversion) and time preferences were noted for the construction of the conceptual model and anticipating pilot study results.

For refinement of psychological variables and observing their relationship with the debt behaviour a preliminary field study was conducted. Bivariate correlations among independent variables including financial literacy, risk aversion, time horizon, decision making style, compulsive buying, money attitudes, Big Five traits, locus of control and social sanctions and the dependent variable (debt behaviour) were estimated. Also, the link between experience of adverse life events and debt behaviour was investigated. Results for this preliminary analysis was as follows:

There were significant differences among groups (good or bad credit status) in terms of experience of adverse life events. Variables that demonstrated significant link with the independent variables were risk aversion, time horizon, compulsive buying, money attitudes (retention) and 2 sub-dimensions of social sanctions.

This pilot study did not disclose enough proof to analyse the relationship of some independent variables between the dependent variable. This might stem from relatively small sample size or the scales utilised for this study. Factor analysis results were problematic regarding the Big Five. Because of the mixed results, more support from literature was needed. For this purpose, literature was reviewed in a systematic manner in order to provide more support for the construction of the conceptual model. Systematic literature review, outputs of semi-structured interviews and this preliminary study were synthesized to develop the models and hypotheses of the study. Some important findings for systematic review is as follows:

Associated with the credit risk assessment, it was observed that reviewed papers approached the phenomenon from different aspects. Therefore, different depended variables were observed. Under the dependent variable category four main types of outcome domain were revealed: Probability of default (32), probability of over-indebtedness (problem debt) (46), financial behaviour (responsibility) (26) and credit misuse (11). Some studies examined more than one dependent variable, hence the total number may not add to the total number of articles examined (108).

Self-control and emotional stability were significant determinants of the dependent variable in whole studies they were examined. 67% of the articles reported significant statistics for self-efficacy, 60% for openness to experience, 71% for impulsiveness, 67% for self-esteem, 75% for optimism, 83% for extraversion, 64% for conscientiousness, 60% for agreeableness, and 50% for neuroticism.

Social motivation / attitudes towards debt (others), attitudes towards loan repayment, consumer behaviour / expenditure pattern, perceived financial well-being, economic socialisation and religious practices were constantly discovered as significant determinants in entire studies they were examined. 69% of studies reported significant effects for financial literacy, 75% for risk aversion, 80% for delay of gratification, 83% for attitudes towards money, 80% for compulsive buying, 85% for attitudes towards credit use, 87% for financial management and 64% for locus of control. Consistently with the focus group findings and pilot study, considerable number of studies (90%), analysed within the scope of the systematic review, indicated that situational variables had significant effect on outcome domain.

Socioeconomic variables analysed and revealed significant effect on the dependent variables comprised of income, employment status, family income, household type, number of children, family income, length of employment, number of dependents, occupational class, household size, education, wealth and social class. Wealth was a significant predictor of outcome variable in all studies it was assessed. Employment status, social class and family income were found significant influencers of the dependent variable in more than 70% of the total articles.

Similar to previous findings of focus group, semi-structured interviews and literature review revealed that family life cycle, age, marital status and gender were commonly examined and implemented demographic variables. More than half of the studies reported significant findings for age and marital status. It was also a considerable finding that family life cycle stage was consistently influencer of probability of default in all studies it was mentioned.

A wide list of factors derived from systematic literature review. Some of them were consistent with the previous findings such as length of the relationship with bank, debt to income ratio, type / diversity of credits used. Furthermore, in spite of the different terminology, variables that were captured in focus group and systematic review process were derived from each other. Whole articles within the scope of this review reported significant influence of length of the relationship with bank, debt to income ratio, type / diversity of credits used and behind schedule payments on the outcome domain. 90% of the studies reported that number of credit cards was a significant indicator, while 88% of articles indicated that past credit behaviour was significantly determined probability of default.

Summary of Quantitative Findings

Depending on the outcomes of research steps aforementioned, hypotheses of the study were specified as follows:

H1a: Self-control has significant impact on debt behaviour

H1b: Conscientiousness has significant impact on debt behaviour

H1c: Emotional stability has significant impact on debt behaviour

H1d: Extraversion has significant impact on debt behaviour

H2a: Risk aversion has significant impact on debt behaviour

H2b: Attitudes towards money (power & prestige) has significant impact on debt behaviour

H2c: Attitudes towards money (retention) has significant impact on debt behaviour

H2d: Financial management behaviour has significant impact on debt behaviour

H2e: Social sanctions have significant impact on debt behaviour

H2f: Social motivation has significant impact on debt behaviour

H2g: Spending behaviour has significant impact on debt behaviour

H2h: Risky credit behaviour has significant impact on debt behaviour

H3: Experiencing adverse life events has significant impact on debt behaviour

H4a: Number of dependents has significant impact on debt behaviour

H4b: Education has significant impact on debt behaviour

H4c: Employment status has significant impact on debt behaviour

H4d: Occupational class (jobclass_2) has significant impact on debt behaviour

H4e: Income has significant impact on debt behaviour

H4f: Perceived wealth has significant impact on debt behaviour

H5a: Gender has significant impact on debt behaviour

H5b: Age has significant impact on debt behaviour

H5c: Marital status has significant impact on debt behaviour

H6a: Number of credit cards that exceeded the spending limit has significant impact on debt behaviour

H6b: Debt to income ratio has significant impact on debt behaviour

H6c: Number of declined credit applications has significant impact on debt behaviour

H6d: Number of successfully repaid credits has significant impact on debt behaviour

Practical purpose of this decision support system is to consider psychometric data in the case of lack of financial knowledge and enough sociodemographic data supporting credit risk assessment of applicants. Hence, three separate models examining the effect of the underlying factors on debt behaviour (good / bad) were proposed. Antecedents and their impact on problematic debt behaviour were examined with the guidance of the developed hypotheses. Hypotheses and conceptual models constructed were tested by means of applying Logistic Regression analysis. For testing the models, data was collected by means of a well-structured questionnaire and face-to-face administration method. Convenience sampling technique was used to choose participants of the study. Having a response rate of 82%, 425 usable questionnaires were obtained. Hence, ultimate sample size of the study was 425.

Findings for Model_1

This model incorporated psychological and situational variables in order to find best set of predictors discriminating individuals' level of credit risk so as to construct a psychometric credit scoring mechanism.

Overall prediction accuracy of the model was 86.2% which means model successfully predicted 86.2% of the cases. When compared with the beginning block representing 74.9% classification performance, there was considerable improvement in prediction accuracy.

Among variables examined experience of adverse life events, risky credit behaviour, conscientiousness, neuroticism, social motivation, financial management and risk aversion contributed to explain the debt behaviour. Strongest influencer was the experience of adverse life events as almost 22 times increased the credit risk of individuals.

Consequently, hypotheses comprising of H1b, H1c, H2a, H2d, H2f, H2h and H3 were accepted.

Findings for Model_2

This model integrates some financial, demographic and socioeconomic variables in order to explore best combination of predictors discriminating applicants with high level of risk for establishing a credit scoring model. These predictors are usually utilized for constructing conventional credit scoring systems with financial data and past financial behaviour.

Overall prediction of the model was 96.2% indicating that model was able to perform 96.2% accurate predictions of individuals credit risk. In comparison to beginning classification with 75.6% correct predictions, model performance was considerably enhanced as a result of inclusion of the six independent variables.

Among variables examined gender, education, occupational class, debt-to-income ratio, number of rejected credits and perceived wealth status contributed to the model. Debt-to-income ratio and number of rejected credits were important predictors as among different categories of these variables credit risk dramatically increased.

As a result, hypotheses including H4b, H4d, H4f, H5a, H6b and H6c were accepted.

<u>Findings for Model_3</u>

In order to analyse and explore the most powerful set of predictors explaining the dependent variable psychometric and financial variables of model 2 and model 3 were incorporated into a single model (model 3). This model was expected to contribute observing the effect of each predictor when they were all taken into account.

Overall prediction of the model was 95.8% which signifies that model was able to classify 95.85% of cases accurately. In comparison to beginning classification with 74.8% correct predictions, model performance was considerably enhanced as a result of inclusion of the twelve independent variables.

List of variables contributed to distinguish individuals in good or bad credit status were as follows: employment status, number of rejected credits, number of successfully repaid credits, perceived wealth status, experience of adverse life events, social sanctions, risky credit behaviour, conscientiousness, attitudes towards money_retention, neuroticism, social motivation and financial management. Among financial variables impact of number of rejected credits was considerable and other financial or socioeconomic indicators very slightly contributed to explain the change in the dependent variable. On the other hand, impact of a number of psychometric variables was very strong. Such as, adverse life events increased being in risky status 53 times, social motivation 17 times and risky credit behaviour 7 times. Neuroticism and conscientiousness also had considerable influence.

Consequently, Model 3 tested all of the hypotheses developed for the study and as a result H1b, H1c, H2c, H2d, H2e, H2f, H2h and H3, H4c, H6c and H6d were accepted.

Regarding the model performances, Table 56 below represents classification performance of model_1, model_2 and model_3. It is observed that, model having the best classification performance is model_2 which employs financial variables. Model_3 has the best classification performance for true negatives as model predicts 97.5% of good cases correctly. It is important to meet more people with financial services for financial institutions aiming profit. Therefore, accuracy in predicting creditworthiness is critical. Hence, model_3 incorporating psychometric variables as well, can support credit risk assessment mechanisms according to strategies and business models of institutions. On the other hand, model_2 is better at predicting true positives which eliminates risks stemming from defaulted loans. Model_1 has relatively lower classification performance confirming the literature findings regarding the use of psychometric tests. It is advised to use psychometric tests as supportive and complementary mechanisms in the case of credit risk assessment. Accordingly, model_1 or model_3 can be used as a secondary screening mechanism for revaluating applicants having scores slightly less or more than the threshold value in order to provide performance improvement. When psychometric tests are employed, hybrid credit scores can be produced. In the case of hybrid scoring weights for psychometric and financial assessments were defined as 70.9% and 29.1%, respectively.

Table 56
Final Classification Table for Models

Model_1	**Observed**		**Predicted**		
			DEBT.Debt behaviour		**Percentage Correct**
			GOOD	BAD	
Step 1	DEBT.Debt behaviour	GOOD	287	27	91.4
		BAD	31	74	70.5
	Overall Percentage				86.2
	a. The cut value is .500				
Model_2	**Observed**		**Predicted**		
			DEBT.Debt behaviour		**Percentage Correct**
			GOOD	BAD	
Step 1	DEBT.Debt behaviour	GOOD	307	9	97.2
		BAD	7	95	93.1
	Overall Percentage				96.2
	a. The cut value is .500				
Model_3	**Observed**		**Predicted**		
			DEBT.Debt behaviour		**Percentage Correct**
			GOOD	BAD	
Step 1	DEBT.Debt behaviour	GOOD	310	8	97,5

		BAD	10	97	90.7
	Overall Percentage				95.8
	a. The cut value is .500				

Contributions of the Research

The literature in credit scoring decision support systems has recently focused on the integration of alternative data sources for building credit risk models. Theoretical studies emphasised the interdisciplinary nature of the phenomenon and heavily investigated the factors influencing debt behaviour from financial, social and psychological aspects. Most of the studies were performed by Western scholars and investigated developed nations. Studies revealed that no technique or mix of variables is superior to another and to establish high performing models context specific factors should be considered.

In the literature, the use of alternative methods in credit scoring has been investigated in this field, especially in developing countries and it has been observed that the emphasis for the improvement is on this field. Small-scale lenders, financiers, or retailers have the potential to benefit greatly from credit decision support systems used mainly by banks. However, studies in this area are limited in terms of proposing theoretical models that will fit these situations. In the case of Turkey, it is observed that various approaches such as psychometric assessment, which is an alternative method in this field is tried to be adapted by a few institutions using standard software packages. However, these standard tools are not compatible with the country dynamics and cultural background.

Specifically, the main contribution of this study is to analyse which indicators explored from the literature can contribute to assess creditworthiness and which new indicators specific to country's economic, social and cultural background can be incorporated into credit risk models for increasing prediction accuracy. This set of variables explored through qualitative and quantitative research procedures can be considered by the theoretical studies for adoption to similar contexts. Psychological scales were used for the field study in this research. Instead of using psychological scales, the related information such as financial management behaviour and risky credit behaviour from financial history or alternative sources such as e-commerce profile which should be assessed from the practitioners' point of view in the case of implementation.

Secondly, theoretical studies focused on integration of socioeconomic, demographic, personality, behavioural and situational factors is limited and they considered limited number of variables. The investigation of this study was comprehensive enough and revealed a broad picture for assessing creditworthiness.

A number of psychological factors' and situational factors' impact were considerably strong and a psychometric scoring model can be implemented for improving prediction accuracy and providing risk assessment for unbanked individuals. Practical tests in this field is very limited and have origins in developed countries. Hence, an important step in Turkish consumer credit market can be establishment of a psychometric scoring model considering the outcomes of this research. Existing systems can be improved by considering some findings directly for increasing performance of decision making process as well. Qualitative investigations have also integrated the practitioners' point of view improved understanding for applicability in the practical field.

Directions for Future Research

There are some limitations associated with empirical part of the research. This study used convenience sampling, which is a kind of non-probability sampling technique aiming to choose the participants based on practical concerns. Although non-probability sampling has limitations due to subjectivity in sample selection and representation of the population, it was used because of dealing with large population, practical reasons and budget and time constraints. It is therefore, is not possible drawing inferences regarding the whole population. Future research in this area may focus on collecting data with probability sampling and may consider a larger sample size. Although this study employed a sufficient sample size for the implemented model, achievement of a larger sample size has potential of enabling novel machine learning methods such as ensemble and hybrid learning approaches. This study used the industry standard Logistic Regression for building credit risk models. However, construction of models with other techniques and their performance comparison with regard to Logistic Regression is an important future direction.

This study depends on self-reported data, which constitutes one of the methodological limitations of the research. Some information that can easily be accessed by financial institutions such as financial ratios and sociodemographic profile is assessed by asking the relevant information to participants due to practical and legal issues encountered during the study. If verification of this kind of data by the cooperation of financial institutions can be provided, one important methodological concern can be addressed. Utilisation of a real credit dataset is important for further testing the models.

Regarding the other psychological variables, application of long tests with a number of questions cannot be practical and answers are open to manipulation when applied at application stage. However, one important direction for the related disciplines might be the transformation of the questions to easily representable images, items and stories to be applied in online form. Items acquiring data associated with the psychological variables should be verified by the relevant fields of study.

This research provided a theoretical framework by defining the parameters and their weights. Future research can also construct models based on broad indicator set that was eliminated for this study and test with different analysis techniques to adopt to different contexts.

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APPENDICES

Appendix 1

Evrak Tarih ve Sayısı: 13/12/2018-E.15921

BEL94MMBH

T.C.
SAKARYA ÜNİVERSİTESİ REKTÖRLÜĞÜ
Etik Kurulu

Sayı : 61923333/050.99/
Konu : 07/04 Arş. Gör. Büşra ALMA ÇALLI

Sayın Arş. Gör. Büşra ALMA ÇALLI

İlgi : Büşra ALMA ÇALLI 05/11/2018 tarihli ve 0 sayılı yazı

Üniversitemiz Sosyal ve Beşeri Bilimler Etik Kurulu Başkanlığının 12.12.2018 tarihli ve 07 sayılı toplantısında alınan "04" nolu karar örneği ekte sunulmuştur.
Bilgilerinizi rica ederim.

Prof.Dr. Arif BİLGİN
Etik Kurulu Başkanı

4. Arş. Gör. Büşra ALMA ÇALLI'nın "Perakende Sektöründe Kredi Değerlendirmeye Yönelik Karar Destek Amaçlı Entegre Bilişim Sistemi Mimarisi Örneği" başlıklı çalışması görüşmeye açıldı.
Yapılan görüşmeler sonunda; Arş. Gör. Büşra ALMA ÇALLI'nın "Perakende Sektöründe Kredi Değerlendirmeye Yönelik Karar Destek Amaçlı Entegre Bilişim Sistemi Mimarisi Örneği" başlıklı çalışmasının Etik açıdan uygun olduğuna oy birliği ile karar verildi.

Evrakı Doğrulamak İçin : http://193.140.253.232/envision.Sorgula/BelgeDogrulama.aspx?V=BEL94MMBH

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Appendix 2

Değerli Katılımcı;

Anket No:

Bu anket formu bireysel kredi kullanıcılarının borç geri ödeme performansına etki eden kişilik, değer ve tutumla ilgili özelliklerinin belirlenmesini amaçlamaktadır. Bu anketten elde edilecek bilgiler bilimsel bir çalışmaya temel oluşturacak ve başka bir amaçla kullanılmayacaktır. Zaman ayırıp bu formu doldurarak, çalışmamıza yapacağınız önemli destek ve katkılarınızdan dolayı teşekkür ederiz.

Saygılarımızla.

Bölüm 1: BİREYSEL

Cinsiyetiniz?	☐ Erkek ☐ Kadın
Yaşınız?	☐ 18-23 ☐ 36-41 ☐ 24-29 ☐ 42-47 ☐ 30-35 ☐ 48 ve üzeri
Medeni Haliniz?	☐ Bekar ☐ Evli ☐ Diğer:………
Evliyseniz aile yaşamınız hangi durumdadır? *(Birden Çok Seçenek Seçebilirsiniz)*	☐ Evli (Çocuksuz) ☐ Okul Öncesi Çocuğu Olan Aile (0 – 6 Yaş) ☐ Okul Çağında Çocukları Olan Aile (7 – 13 Yaş) ☐ Ergen Çocukları Olan Aile (14 – 20 Yaş) ☐ Genç Erişkinler Yetiştiren Aile ☐ Anne – Baba (Çocukların evden ayrıldığı dönem)
Çocuk Sayısı	……………*(Lütfen Belirtiniz)*
Eğitiminiz? *(Mezuniyete Göre)*	☐ İlkokul ☐ Ortaokul / İlköğretim ☐ Lise ☐ Üniversite ☐ Lisans Üstü
Çalışma Durumunuz	☐ Düzenli bir işte çalışıyorum (*kalıcı pozisyon, sözleşmeli*) ☐ Bağımsız çalışanım (*Serbest meslek*) ☐ Emekliyim ☐ Çalışmıyorum ☐ Diğer : …………………………………. *(Lütfen Belirtiniz)*
Meslek	☐ Memur ☐ Öğretmen ☐ İşçi ☐ Mimar / Mühendis ☐ Emekli ☐ Öğrenci ☐ Esnaf ☐ Muhasebeci ☐ Serbest Çalışan ☐ Avukat ☐ Çiftçi ☐ Çalışmıyor ☐ Ev Hanımı ☐ Diğer:………………
İşinizde Ne Kadar Süredir Çalışıyorsunuz?	☐ 1 yıldan az ☐ 1-5 Yıl ☐ 6-10 Yıl ☐ 11-15 Yıl ☐ 16 yıl ve üzeri
Son 10 Yılda Kaç Defa İş Değiştirdiniz:	……………………… *(Lütfen Belirtiniz)*
Yönetici Pozisyonunda Çalışıyor musunuz?	☐ Evet ☐ Hayır
***Yöneticiyseniz* Hangi Pozisyonda Çalışıyorsunuz**	……………………………………… *(Lütfen Belirtiniz)*
Bakmakla Yükümlü Olduğunuz Kişi Sayısı Nedir? (Siz Hariç)	☐ Yok ☐ 1 Kişi ☐ 2 Kişi ☐ 3 Kişi ☐ 4 Kişi ve Üzeri
Oturduğunuz Ev	☐ Kendi Evim ☐ Kira Ödüyorum ☐ Kurum, Lojman vb. ☐ Aileme Ait ☐ Diğerleriyle (Aile, Arkadaşlar veya Akrabalar ile yaşıyorum) ☐ Diğer…………………………………………… *(Lütfen Belirtiniz)*
Aylık Kişisel Geliriniz	☐ 1600 TL'den az ☐ 1,601 - 3,000 TL ☐ 3,001 - 4,500 TL ☐ 4,501 - 6,000 TL ☐ 6,001 - 7,500 TL ☐ 7,501 - 9,000 TL ☐ 9,001 TL ve üzeri
Hanenizin Aylık Ortalama Geliri	☐ 1600 TL'den az ☐ 1,601 - 4,500 TL ☐ 4,501 - 7,500 TL ☐ 7,501 - 10,000 TL ☐ 10,001 - 13,500 TL ☐ 13,501 - 15,000 TL ☐ 15,001 TL ve üzeri

Bölüm 2: KREDİ KARTI KULLANIMI ve HARCAMA ALIŞKANLIKLARI

Aktif Olarak Kullandığınız Kredi Kartı Sayısı	☐ Hiç yoktur ☐ 1 Adet ☐ 2-4 Adet ☐ 5-7 Adet ☐ 8 Adet ve Üzeri	**Şu an limiti biten kredi kartı sayısı:**	……………… *(Lütfen Belirtin)*

Lütfen aşağıdaki ifadeleri değerlendiriniz		1 Hiçbir Zaman	2 Çok Nadiren	3 Ara Sıra	4 Genellikle	5 Her Zaman
	Kredi Kartı Kullanımı					
1-)	Kredi kartı harcamalarım kredi kartı limitime yakın düzeydedir	☐	☐	☐	☐	☐
2-)	Kredi kartı borcumu başka kredi kartımla / kartlarımla öderim	☐	☐	☐	☐	☐
3-)	Kredi kartlarımda borcun tamamı yerine asgari ödeme tutarını öderim	☐	☐	☐	☐	☐
4-)	Kredi kartı ödemelerimi geciktiririm	☐	☐	☐	☐	☐
5-)	Kredi kartımdan nakit para çekerim	☐	☐	☐	☐	☐
6-)	Kredi kartı borcumu ödemek için banka kredisi kullanmak zorunda kalırım	☐	☐	☐	☐	☐
7-)	Kredi kartı borcumu ödemek için yakınlarımdan borç almak zorunda kalırım	☐	☐	☐	☐	☐
	Harcama Alışkanlıkları					
1-)	Ay sonunda param varsa, onu harcamak zorunda hissederim	☐	☐	☐	☐	☐
2-)	Düşünmeden satın alırım	☐	☐	☐	☐	☐
3-)	Ödemekte zorlanacağım şeyleri satın alırım	☐	☐	☐	☐	☐
4-)	Kendimi daha iyi hissetmek için sık sık bir şeyler alırım	☐	☐	☐	☐	☐
5-)	Alışveriş yapmadığım günlerde huzursuz hissederim	☐	☐	☐	☐	☐
6-)	Kredi kartımın sadece asgari ödeme tutarını öderim	☐	☐	☐	☐	☐
7-)	Kredi kartlarımın son ödeme tarihinde aylık toplam borç tutarını ödemeye yetecek kadar param yoktur	☐	☐	☐	☐	☐

Son 6 ay içerisinde aşağıdaki aktiviteleri yapma sıklığınızı dikkate alarak ifadeleri değerlendiriniz		1 Hiçbir Zaman	2 Çok Nadiren	3 Ara Sıra	4 Genellikle	5 Her Zaman
	Finansal Davranış					
1-)	Bütün faturalarımı zamanında ödemeye çalıştım	☐	☐	☐	☐	☐
2-)	Aylık harcamalarımın hesabını yaptım	☐	☐	☐	☐	☐
3-)	Bütçem veya harcama planıma uygun hareket ettim	☐	☐	☐	☐	☐
4-)	Kredi kartımın / kartlarımın limitini tükettim	☐	☐	☐	☐	☐
5-)	Kredi kartım için sadece minimum tutarda ödeme yaptım	☐	☐	☐	☐	☐
6-)	Tasarruf için para biriktirmeye çalıştım	☐	☐	☐	☐	☐
7-)	Uzun vadeli hedeflerim (araba almak, eğitim, ev almak vb.) için tasarruf yaptım	☐	☐	☐	☐	☐
8-)	Pahalı bir ürün veya hizmet satın alırken fiyat karşılaştırması yaptım	☐	☐	☐	☐	☐
9-)	Yatırım yaptım (bireysel emeklilik, hisse senedi, döviz, altın vb.)	☐	☐	☐	☐	☐

Kredi almak <u>iyi</u> bir şeydir. Çünkü… ….	……………………………………………………… *(Lütfen yandaki cümleyi tamamlayın)*
Kredi almak <u>kötü</u> bir şeydir. Çünkü….	……………………………………………………… *(Lütfen yandaki cümleyi tamamlayın)*

	Yoktur	**Aylık Gelirimden Azdır**	**Aylık Gelirime Eşittir**	**Aylık Gelirimin 2 Katıdır**	**Aylık Gelirimin 3 Katıdır**	**Aylık Gelirimin 4 Katıdır**	**Aylık Gelirimin 5 Katıdır**	**Aylık Gelirimin 5 katından fazladır**
Şu Andaki Kredi Kartı Borç Miktarım (*Kredi kartlarınıza ait toplam borcu dikkate alınız*	☐	☐	☐	☐	☐	☐	☐	☐
Şu Andaki Banka Kredisi Borcu Miktarım	☐	☐	☐	☐	☐	☐	☐	☐
Şu Anda Aile/Akraba veya Arkadaşlarıma Olan Borç Miktarım	☐	☐	☐	☐	☐	☐	☐	☐
Şu Andaki Kira Borcu veya Su / Elektrik / Doğalgaz Firmalarına olan Borç Miktarım (*30 günü geçmiş borcunuz varsa dikkate alınız)*	☐	☐	☐	☐	☐	☐	☐	☐

Şu Andaki Toplam Borç Miktarınız?	☐ Yoktur ☐ Aylık gelirimden azdır ☐ Aylık gelirime eşittir ☐ Aylık gelirimin 2 katıdır ☐ Aylık gelirimin 3 katıdır	☐ Aylık gelirimin 4 katıdır ☐ Aylık gelirimin 5 katıdır ☐ Aylık gelirimin 5 katından fazladır ☐ Diğer …………………………..….(*Lütfen TL cinsinden belirtiniz)*

Hiç Kredi Başvurusunda Bulundunuz mu?	☐ Evet ☐ Hayır	**Hiç Kredi Aldınız mı?**	☐ Evet ☐ Hayır
Daha Önce Reddedilen Kredi Başvuru Sayısı	☐ Hiç yoktur ☐ 1 Kez ☐ 2-3 Kez ☐ 4 ve üzeri	**Daha Önce Başarılı Bir Şekilde Ödenen Kredi Sayısı**	☐ Hiç yoktur ☐ 1 Kez ☐ 2-3 Kez ☐ 4 ve üzeri

	Lütfen aşağıdaki ifadeleri Borcunuz Olduğunu Varsayarak değerlendiriniz ***Yaptırım***	**1** **Hiç Katılmıyorum**	**2** **Katılmıyorum**	**3** **Ne Katılıyorum Ne de Katılmıyorum**	**4** **Katılıyorum**	**5** **Tamamen Katılıyorum**
1-)	Çevremde borcum olduğunun duyulması beni *utandırır*	☐	☐	☐	☐	☐
2-)	Borcum yüzünden mahkemelik duruma düştüğümün çevremde duyulması beni *utandırır*	☐	☐	☐	☐	☐
3-)	Borcum yüzünden haciz gelirse çevremden *utanırım*	☐	☐	☐	☐	☐
4-)	Borcum yüzünden çevremin beni *dışlamasından korkarım*	☐	☐	☐	☐	☐
5-)	Borcum yüzünden mahkemelik duruma düşersem çevremin beni *dışlamasından korkarım*	☐	☐	☐	☐	☐
6-)	Borcum yüzünden haciz gelirse çevremin beni *dışlamasından korkarım*	☐	☐	☐	☐	☐
7-)	Borcum yüzünden çevremde *itibarımı* kaybetmekten korkarım	☐	☐	☐	☐	☐
8-)	Borcumla yüzünden mahkemelik duruma düşersem çevremde *itibarımı* kaybetmekten korkarım	☐	☐	☐	☐	☐
9-)	Borcumu ödemediğim için mahkemelik duruma düşmek beni *korkutur*	☐	☐	☐	☐	☐
10-)	Borcumu ödemediğim için hapse girmek beni *korkutur*	☐	☐	☐	☐	☐
11-)	Borç tahsil bürolarından gelecek aramalar beni *korkutur*	☐	☐	☐	☐	☐

Kişisel Tasarruf Seviyenizi Nasıl Değerlendiriyorsunuz?	☐ Çok Kötü ☐ Kötü ☐ Orta ☐ İyi ☐ Çok İyi	1-) Tüm Varlıklarız, 2-) Yatırımlarınız, 3-) Nakit Paranız ve 4-) Borçlarınızı Düşündüğünüzde *Genel Refah Düzeyinizi* Nasıl Değerlendiriyorsunuz?	☐ Çok Kötü ☐ Kötü ☐ Orta ☐ İyi ☐ Çok İyi

	Lütfen aşağıdaki ifadeleri değerlendiriniz ***Kredi Kullanımı***	**1** **Hiç Katılmıyorum**	**2** **Katılmıyorum**	**3** **Ne Katılıyorum Ne de Katılmıyorum**	**4** **Katılıyorum**	**5** **Tamamen Katılıyorum**
1-)	Kredi kullanırken veya borçlanırken, hayatımda önem verdiğim insanlar dikkatli davranmam gerektiğini düşünür	☐	☐	☐	☐	☐
2-)	Çevremdeki insanlar kredi kullanırken veya borçlanırken dikkatli davranmam gerektiğini düşünür	☐	☐	☐	☐	☐
3-)	Ailem ve arkadaşlarım kredi kullanımı veya borçlanmayla ilgili nasıl davranmam gerektiğini düşünüyorlarsa o şekilde davranmak isterim	☐	☐	☐	☐	☐

Harcama Davranışları

1-)	İnsanlara işimi yaptırmak için parayı kullanırım	☐	☐	☐	☐	☐
2-)	Satın aldığım şeyleri insanları etkilemek için alırım	☐	☐	☐	☐	☐
3-)	İnsanları etkilemek için pahalı şeyler satın alırım	☐	☐	☐	☐	☐
4-)	Paranın başarının temel göstergesi olduğunu düşünürüm	☐	☐	☐	☐	☐
5-)	Bazen sahip olduğum parayla övünürüm	☐	☐	☐	☐	☐
6-)	Parayı kendimi iyi hissetmek için harcarım	☐	☐	☐	☐	☐
7-)	Gelecek için finansal planlama yaparım	☐	☐	☐	☐	☐
8-)	Gelecek için düzenli olarak kenara para koyarım	☐	☐	☐	☐	☐
9-)	Yaşlılığımda sıkıntı çekmemek için para biriktiririm	☐	☐	☐	☐	☐
10-)	Bütçemi dikkatli bir şekilde takip ederim	☐	☐	☐	☐	☐

Alışkanlıklar

1-)	Kötü olduğunu düşündüğüm alışkanlıklardan vazgeçmekte zorlanırım	☐	☐	☐	☐	☐
2-)	Anlık olarak iyi hissettiren fakat sonradan pişmanlık duyduğum şeyleri yaparım	☐	☐	☐	☐	☐
3-)	Cazip gelen fakat sonucunun kötü olacağını tahmin ettiğim durumlarda kontrollü davranırım	☐	☐	☐	☐	☐
4-)	Sonucunun iyi ya da kötü olduğunu düşünmeden davranabilirim	☐	☐	☐	☐	☐
5-)	Dikkatim çabuk dağılır	☐	☐	☐	☐	☐

	Hiç Olmaz	**Bazen Olur**	**Her Zaman Olur**
Borcunuzun Ödemesini Geciktirdiğiniz Olur Mu? (*Kredi Kartı ya da Kredi Ödemesi Vb.*)	☐	☐	☐
Borcunuzu Ödemediğiniz için *Faiz* ya da Ceza Ödemek Zorunda Kalır Mısınız?	☐	☐	☐

	Hiç Olmadı	**1 Kez Oldu**	**2 veya Daha Fazla Oldu**
Ödeme Günü Gelmiş Borcunuzun Ödemesini 90 Günden Fazla Geciktirdiniz mi?	☐	☐	☐
Borcunuzu Ödemediğiniz için Mahkemelik/İcra Takibine Düştüğünüz mü?	☐	☐	☐
Borcunuzu Ödemediğiniz İçin Mallarınıza Haciz Geldi mi?	☐	☐	☐

1-) *Gecikme Faizi ya da Ceza Ödemek* **2-)** *90 Günden Fazla Borçlu Kalmak* **3-)** *Mahkeme / İcra / Haciz* **Yukarıdaki durumlarından birini en az bir kez yaşadım çünkü….** *(Birden çok seçenek işaretleyebilirsiniz)*	☐ *Böyle Bir Durum Yaşamadım* ☐ Boşanmıştım ☐ Eşim ya da çocuğum vefat etmişti ☐ Önemli bir sağlık problemim vardı ☐ İşten çıkmıştım/çıkarılmıştım ☐ Hapse girmiştim ☐ Taşınmıştım	☐ Evlenmiştim ☐ Yakın akrabalarımdan biri vefat etmişti ☐ Ailemden birinin önemli bir sağlık problemi vardı ☐ Beklemediğim sağlık masrafları oldu ☐ İflas etmiştim ☐ Eşimin işiyle ilgili problemler oldu ☐ Diğer………………*(Lütfen Belirtiniz)*	

Bölüm 3: KİŞİLİK VE TUTUMLAR **Lütfen Aşağıdaki İfadeleri Değerlendiriniz**		1 Hiç Katılmıyorum	2 Katılmıyorum	3 Ne Katılıyorum Ne de Katılmıyorum	4 Katılıyorum	5 Tamamen Katılıyorum
1-)	Tanımadığım kişilerle konuşmaktan kaçınırım	☐	☐	☐	☐	☐
2-)	Değişimle dolu, öngörülemeyen bir yaşam biçimindense; rutin bir yaşamı tercih ederim	☐	☐	☐	☐	☐
3-)	Kendimi risk alan bir kişi olarak tanımlamam	☐	☐	☐	☐	☐
4-)	Hata yapmamak için, işimi şansa bırakmayı sevmem	☐	☐	☐	☐	☐
5-)	Paramı harcama konusunda çok dikkatliyimdir	☐	☐	☐	☐	☐
6-)	Yeni şeyleri deneyen ilk kişi ben olurum	☐	☐	☐	☐	☐

Lütfen Aşağıdaki İfadeleri Değerlendiriniz		1 Hiç Katılmıyorum	2 Katılmıyorum	3 Ne Katılıyorum Ne de Katılmıyorum	4 Katılıyorum	5 Tamamen Katılıyorum
1-)	Herhangi bir işi eksiksiz yapmaya gayret ederim	☐	☐	☐	☐	☐
2-)	Dikkatsiz davranırım	☐	☐	☐	☐	☐
3-)	Bir görevin (çalışma, ödev, iş) verilmesi için güvenilir biriyim.	☐	☐	☐	☐	☐
4-)	Dağınık olmaya yatkın biriyim	☐	☐	☐	☐	☐
5-)	Tembel olmaya eğilimliyim	☐	☐	☐	☐	☐
6-)	Bir işi bitirene kadar azimle çalışan biriyim	☐	☐	☐	☐	☐
7-)	Verimli çalışan biriyim	☐	☐	☐	☐	☐
8-)	Plan yapar ve bu planları uygularım	☐	☐	☐	☐	☐
9-)	Dikkatim çabuk dağılır	☐	☐	☐	☐	☐
10-)	Karamsar, hüzünlü biriyim	☐	☐	☐	☐	☐
11-)	Rahatım, strese girmem	☐	☐	☐	☐	☐
12-)	Gergin biriyim	☐	☐	☐	☐	☐
13-)	Endişeli biriyim	☐	☐	☐	☐	☐
14-)	Duygusal olarak dengeliyim, kolay kolay mutsuz olmam	☐	☐	☐	☐	☐
15-)	Ruhsal durumu çabuk değişen biriyim	☐	☐	☐	☐	☐
16-)	Gergin durumlarda, ortamlarda sakin kalabilirim	☐	☐	☐	☐	☐
17-)	Kolayca sinirlenen biriyim	☐	☐	☐	☐	☐
19-)	Konuşkan biriyim.	☐	☐	☐	☐	☐
20-)	İçine kapanık biriyim	☐	☐	☐	☐	☐
21-)	Enerjik biriyim	☐	☐	☐	☐	☐
22-)	Diğer insanları heveslendiririm	☐	☐	☐	☐	☐
23-)	Kendine güveni olan biriyim	☐	☐	☐	☐	☐
24-)	Dışa dönük, sosyal biriyim	☐	☐	☐	☐	☐
25-)	Bazen utangaç ve çekingenim	☐	☐	☐	☐	☐
26-)	Suskun biriyim	☐	☐	☐	☐	☐

☺

Değerli Katkılarınızdan Dolayı
Teşekkür Ederiz

Appendix 3

REFERENCE	DEPENDENT VARIABLE	VARIABLES EXAMINED	MAIN FINDINGS (SIGNIFICANT)	SAMPLE SIZE N=	OTHER SAMPLE CHARACTERISTICS	COUNTRY	DESIGN (Cross sectional, Longtitudional)	ANALYSIS TYPE
Gray (1985)	Probability of default	ethnicity, marital status, family income, credit hours earned, GPA, educational debt, number of educational debt, other debt, number of other debt, field of study	ethnicity_black (+), marital status_other (+), educational debt (+) , number of educational debt (+), field of study_College of Arts and Science (+), family income (-), credit hours earned (-), marital status_married (-), GPA (-)	650	Students (Federal Insured Loan Borrowers)	U.S.	Longtitudinal	Multiple logistic regression analysis
Dessart & Kuylen (1986)	Problematic debt (registration of arrears)	Instutitional Number of outstanding credits, distribution channel_intermediary, credit score Socioeconomic Income, family life cycle, home ownership, main source of income, marital status, number of insurance policies, length of employment ,existence of financial liabilities to mail order companies, financial reserve/ additional income, number of expensive consumer durables, number of bank accounts, income pattern, ownership of a boat Psychological locus of control, time orientation, deferring satisfaction, view of financial management Decision-behaviour financial knowledge, perceived importance of reliability of financial institution, perceived importance of term of credit, perceived importance of low interest rate	Instutitional Number of outstanding credits (+), distribution channel_intermediary (+), credit score Socioeconomic income (-), family life cycle_children 7-18 age group (+), home ownership_tenants (+), main source of income_unemployment benefit (+), marital status_widow/divorced, number of insurance policies (-), length of employment (-),existence of financial liabilities to mail order companies (+), financial reserve/ additional income (-), number of expensive consumer durables (-), number of bank accounts 2 or less (-), income pattern_irregular (+), ownership of a boat (-) Psychological locus of control_external (+), time orientation_future/past (+), deferring satisfaction (-), view of financial management_important (-) Decision-behaviour financial knowledge_moderate (-), perceived importance of reliability of financial institution (-), perceived importance of term of credit (-), perceived importance of low interest rate (-),	901	Dutch nationals with consumer credits (registered to Credit Registration Bureau)	Netherlands	Longtitudinal	Corelation analysis
Wilms, Moore & Bolus (1987)	Probability of default	ethnicity, gender, citizenship, average annual income, prior education, program of study, program completion, average loan amount, institutional characterisitcs (average fulltime enrollment, percentage of student body white, percentage of GSL borrowers to total school enrollment)	ethnicity_black (+), citizenship_U.S. citizen (+), average annual income (-), prior education_high school graduate (-), program of study_other (+), program completion_completed (-), institutional characteristics (average fulltime enrollment)_enrolled in proprietary school (+)	4617	Students (California Institutions & students with high default rates)	U.S.	Cross-sectional	Discriminant analysis

Gardner & Mills (1989)	Probability of default (default of delinquent files)	loan-to-value (LIV) ratio, initial payment-to-income (P/I) ratio, balance-to-value at delinquency, loan-to-purchase price, original maturity of the loan, age of the loan at delinquency, loan purpose, contract rate of interest, age of property, property location (a proxy for local economic con-ditions), employment status (occupation), age, number of dependents, credit record, date of delinquency, change in marital status, change in occupation, reason of delinquency, existence of previous delinquencies, property conditions, gender, marital status, property occupancy at application, age	loan-to-value (LIV) ratio (+), balance-to-value at delinquency (+) ,property location (a proxy for local economic conditions)_rural & blue collar cities (+), employment status (occupation)_less stable income (self-employed and sales) (+), date of delinquency_1980-1981 (+), reason of delinquency (loss job, illness/death, financial/legal problems) (+), existence of previous delinquencies_yes (+)	713	owners of delinquent loans (conventional loans)	U.S.	Cross-sectional	Logistic regression analysis
Greene (1989)	Probability of default	graduation, ethinicty, income, GPA, grant aid, scholarship	graduation (-),income (-), GPA (-), grant aid (+), scholarship aid (+), ethnicity_black (+) NOTE: graduation from high school or drop out	161	Students	U.S.	Cross-sectional	Tobit analysis
Hira (1990)	Problematic debt (households facing debt problems)	gender, household size,employment status, marital status, sources of income, income, total debt, number of sources of borrowing, amount of debt from each source and total monthly debt	employment status_employed (+), number of sources of borrowing (+), marital status_married (+), gender_male (+), household size (+)	404	General population (clients seeking debt readjustment services)	Scotland	Longtitudinal	Variance analysis
Livingstone & Lunt (1992)	Level of debt	income, total amount of savings, amount of regular saving, expenditure, age, social class, education, marital status, family size, home ownership, attitudional factors, psychological factors (economic attribution, locus of control, coping strategies, consumer pleasure, perceived control over finances), adverse life events, attitudes towards credit, self reward with purchase, number of bank accounts	social class_low (+), income (+), number of debts (+), psychological variables (external locus of control (+), attitudes towards credit_useful but complicated (-), general coping_less cool and calm (+)), economic behaviour (self reward with purchase_disagree (+), think about money (+), willing to use credit (+), number of bank accounts (-), enjoy shopping for clothes_disagree (+), shop in favourite shops_disagree (+))	279	Households at Oxford	U.K.	Cross-sectional	Multiple logistic regression analysis

Tokunaga (1993)	Credit misuse	marital status, income, education level, indices of socioeconomic status, gender, ethicity, home ownership, family financial situation, parents' attitudes towards credit use (view of credit, use of forms of credit), risk taking number of life events, last 12 months variables regarding the relationship with money, self-esteem, self-efficacy, locus of control, attitudes towards money, decision making under risk (risk seeking, risk aversion), sensation seeking	External locus of control (+), self-efficacy (-), attitutudes towards money_power prestige (+), attitudes towards money_retention (-), anxiety on financial matters (+), sensation seeking (-), risk taking (-), parents' view towards credit_positive (-), use of forms of credit (-)	131	Individuals who had experienced serious financial problems+ Individuals who had not experienced financial problems (Consumer Credit Counseling Services (CCCS) contacts)	U.S. Northern California	Cross-sectional	Discriminant analysis
Lea, Webley & Levine (1993)	Level of debt	income, socioeconomic status (occupational class), households' financial position, home ownership, children in household, number of friends/family in debt, age, religion, attitudes towards debt, number of debts, adverse economic circumstances, marital status, others' attitudes towards debt	income (-), socioeconomic status (occupational class) (-), households' financial position_difficult (+), home ownerhip_rent (+), children in household (+), number of friends/family in debt (+), attitudes towards debt_permissive (+),number of debts (+), adverse economic circumstances (+), age (-), others' attitudes towards debt_less disapproving (+) religion (significant)	2640	households (non-debtors) households (mild-debtors) households (serious-debtors)	U.K.	Cross-sectional	Multiple logistic regression analysis
Ryan (1993)	Probability of default	would borrow again, financial aid staff utilisation, rights and responsibilites knowledge, family income, current employment related to major, utilisation of councelling center, religion, had to borrow to attend, ease of obtaining account information, GPA, level of father's education, had other financial aid, age	would borrow again_no (+), financial aid staff utilisation_yes (+), rights and responsibilites knowledge (-), family income (-), current employment related to major, utilisation of councelling center (+), religion_yes (-), had to borrow to attend (+), GPA (-), had other financial aid (+)	352	Students (California State University)	U.S.	Cross-sectional	Discriminant analysis
Dynarski (1994)	Probability of default	age, gender, ethnicity, marital status, number of dependents, high school education completion, type of school, highest college degree earned, loan amount, monthly loan payment, income	ethnicity_black (+), high school education completion_did not complete (+), type of school_proprietary or two-years schools (+), highest college degree earned_no degree or certificate (+), income (-)	7613	Students	U.S.	Longtitudinal	Logistic regression analysis

Zhu & Meeks (1994)	Problematic/outstanding debt	employment status, age, attitudes towards credit, education, income, ability to obtain and use credit in the past (in 1983) (5 variables), willingness to use credit (in 1983) (general attitudes, specific attitudes), marital status, family size, ethnicity	age (-), attitudes towards credit_favourable (+), education_high (+), emploment status_full time) (+), outstanding credit balance in the past (+)	618	low income families	U.S.	Longtitudional	Multiple regression analysis
Davies &Lea (1995)	Level of debt	Religion, age, gender, number of credit cards , attitudes towards debt, locus of control, income, expenditure, adverse life events	age (+), number of credit cards (+), attitudes towards debt_pro debt attitude (+), religion_some categories (+), gender_male (+)	140	Undergraduate students	U.K.	Longtitudional	Logistic regression analysis
Lea, Webley & Walker (1995)	Level of debt	locus of control, attitutes towards debt, economic socialisation, social comparisons, use of credit, social support for debt, money management, number of money management facilites, consumer behaviour, time horizon, gender, employment status, number of children, home ownership	gender_female (+), employment status_part time, housewives or unemployed (+), number of children (+), home ownership rent (+), social support for debt (+), economic socialisation_parents well off (+), social comparisons (+), lifestyle_missing appointments (+), money management poor money management skills (+), number of money management facilities (-), consumer behaviour_lower income consumption stye (+), time horizon (-)	2250	Households	U.K.	Cross-sectional	Multiple logistic regression analysis
Webley & Nyhus (1998)	Debt Index	income, change in income, self-reported change in income, income expectations, income uncertainty, household characteristics, age, gender, education, number of children, home ownership, existence of a partner in house, attitudes towards debt, time preferences, self-control, time horizon, money management, economic socialisation, health, conscientiousness	income (-), existence of a partner in house (-), time preferences_delayed payment (+), time horizon (-), self-control_prefer to spend immediately (+)	4147	Secondary data from CentER Saving Survey (CSS)	Dutch households	Longtitudinal (3 years)	Multiple logistic regression analysis
Dunn & Kim (1999)	Probability of default	home ownership, age, education, marital status, number of children, unemployment status of husband/wife, number of missing pay-off minimum amount due (past 6 months), income, number of credit cards reached credit	total minimum required payment from all credit cards to income ratio (+), percentage of total credit line which the customer used (+), number of credit crads on which the customer has charged the credit limit (+), age (-), number of children (+), marital status_single (+)	5384	Households	U.S. (Ohio)	Longtitudional , Household panel survey 16 months (16 time points)	Probit regression analysis

		limits, total amount owed on all credit cards (carried over), total minimum required payment to income, carried balance to income, percentage of total credit line used, debt to income ratio						
Grable & Joe (1999)	Financial behaviour_positive (financial risk tolerance)	gender, age, marital status, income, education, ethnic background, home ownership, number of dependents, financial knowledge, solvency ratio	education (+), income (+), ethnicity_non white (+), financial knowledge (+), home ownership (-), number of dependents (-), financial solvency (+)	220	White collar clerical workers		Cross-sectional	Ordinary least squares regression analysis
Zhang & DeVaney (1999)	Debt repayment behaviour	education, gender, age, length of employment, ethnicity, marital status, home ownership, household size, number of children income, existence of a regular payment, ratio of monthly debt payment to income, the ratio of liquid assets to total debt, the ratio of total debt to total assets, net worth, attitudes towards credit (positive, negative, neutral), time horizon (planning for saving & spending)	age (-), income (-), ethnicity_non white (+), marital status_single (+), number of children (+), home ownership_rent (+), total debt / total assets ratio (+), time horizon (for planning for saving and spending) (-)	2715	Secondary data from 1995 Survey of Consumer Finances	U.S.		Multivariate logistic regression analysis
Godwin (1999)	Probability of debt repayment difficulty	age, gender, household size, marital status, ethnicity, employement status, other debts (credit card, mortgage, auto, durable goods, home improvement), adverse life events (financial supoport from relatives or friends,changes in household composition, large expenditures, illness or disability), employment status, marital status, debt attitudes and behaviour (Approval of various uses of credit_yes), turned down for credit_yes), balked at applying for credit_yes)	age (-), household size (+), ethnicity_non-white (+), debt attitudes and behaviour (Approval of various uses of credit_yes (+), turned down for credit_yes (+), balked at applying for credit_yes (+)), other debts_mortgage (+), other debts_auto debt (+), other debts_durable goods debt (+), adverse life events_financial supoport from relatives or friends (+), adverse life events_sold real estate (+), adverse life events_major improvements in real estate (+)	1479	households	U.S.	Longtitudinal	Logistic regression analysis
Domowitz & Sartain (1999)	Probability of bankruptcy	home ownership, other debts_medical debt, marital status, debt/asset, credit card debt/income, unsecured bank debt/income, unsecured individual debt/income, unsecured other debt/income, secured bank debt/income, secured other debt/income (these ratios are for different types of debt)	other debts_medical debt (+), other debts_credit card debt (+), home ownership_no (+), income & home ownership low&no (+), credit card debt/income (+), unsecured individual debt/income (+)	1862+827	households	U.S.	Cross-sectional	Logistic regression analysis

Fay, Hurst & White (2002)	Probability of bankruptcy	net financial benefit from filling bankruptcy, adverse life events (unemployment, divorce, health problems), family income, change in income, household size, average bankruptcy filling rates, age, education, home ownership, business ownership status, macroeconomic factors (the change in average income in household's state of residence, the standart deviation of income per capita in the state, the unemployment rate in the country of residence)	net financial benefit from filling bankruptcy (+), family income (-), change in income_reduction (-), household size (+) adverse life events_divorce (+), average bankruptcy filling rates (+), age (-), education (-), home ownership_own (-)	254	households	U.S.	Longtitudinal	Probit regression analysis
Chakravarty & Rhee (1999)	Probability of bankruptcy	age, ethnicity, home ownership, income, net financial benefit from filling bankruptcy, wealth, annual consumer/credit card debt, exemption (family's dollar exemption in the state of residene in the year of filling), adverse life events (job loss, divorce, health problems, money management problems, harassment/lawsuit), marital status & gender_single female, number of years of marriage lasted, medical coverage, economic trend variables (% change in state bankrupcy filling, national non-business bankrupcy filling rate), state specific asset exemption amount	age (-), ethnicity_white (-), income (-), net financial benefit from filling bankruptcy (+), wealth (-), annual consumer/credit card debt (+), adverse life events_job loss (+), adverse life events_divorce (+), adverse life events health problems (+), adverse life events_money management problems (+) , adverse life events_harassment/lawsuit (+), length of employment (-), marital status & gender_single female, (+), medical coverage_no (+)	587	households	U.S.	Longtitudional	Multinominal logistic regression
Drentea (2000)	Probability of default & level of debt	Minority, gender, age, education, employement status, income, family life cycle, number of children, debt/income ratio, carry balance, amount of credit used, number of credit cards_3 or more credit cards, previous default, debt stress index	Level of debt age (-), family life cycle_married (+), employment status_have job (+), education (-), income (+), debt stress index (+), family status_married with children (+), family life cycle_single with no children (-), debt/income (+) Probability of default age_below 30 (+), debt stress index (+)	1037	Ohioan households (age over 18)	U.S.	Cross-sectional	Multiple regression analysis

Nyhus & Webley (2001)	Financial behaviour_positive	age, education, income (household net income), family size, partner present in household, gender of head of household, emotional stability, inflexibility, tough-minded, meticulous, ongoing, agreeableness, autonomy, conscientiousness, extraversion	age (+), education (+), autonomy (+), emotional stability (-), meticulous (-), agreeableness (+)	1266 individuals in 734 households	Secondary data from CentER Saving Survey (CSS)	Dutch households	Longtitudinal (2 years)	Logistic regression analysis
Kim & DeVaney (2001)	Problematic/outstanding debt	education, income, real assets, credit card interest rate, number of credit cards, credit limit, attitudes towards credit, behind schedule payments,household size, income expectation, attitudes towards the use of credit for vacation, attitudes towards the use of credit for living expenditure, attitudes towards the use of credit for luxury goods, time horizon	education (-), income (-), real assets (-), liquid assets (-), investment assets (-), credit card interest rate (+), number of credit cards (+), credit limit (-), attitudes towards credit_positive (+), behind schedule payments (+), age_lower than 37 (+), time horizon_more than 5 years (-), attitudes towards credit_positive (+), behind schedule payments (+), attitudes towards the use of credit_for vacation (+)	4846	Households	U.S.	Cross-sectional	Ordinary least squares regression analysis
Chien & DeVaney (2001)	Problematic/outstanding debt	age, household size, education, ethnicity, marital status, occupation_professional status, home ownership, income, liquid assets, attitudes towards credit, specific attitudes towards credit_index	marital status_married (+), occupation_professional status (+), home ownership_rent (+), attitudes towards credit_favorable (+), marital status_married (+), occupation_professional status (+), home ownership_rent (+), attitudes towards credit_index (+), household size (+), income (-), education (+)	4305	Households	U.S.	Cross-sectional	Logistic regression
Norvilitis, Szablicki & Wilson (2003)	Level of debt	attitudes towards money, impulsivity, locus of control, life satisfaction, stress, financial well-being, GPA, gender, ethnicity	perceived financial well-being (-)	227	College students	U.S.	Cross-sectional	NR
Baek & Hong (2004)	Level of debt	family life cycle, credit limit, number of credit cards, financial assets, non financial assets, education, employment status, ethinicity, income, home ownership, expected interest rate, spending behaviour, attitudes towards credit, payment pattern_on time, experience of credit rejection, discouraged borrower, savings for future	credit limit (+), number of credit cards (+), income (+), financial assets (-), education (+), savings for future (-), credit limit (+), ethnicity_white (+), payment pattern_on time (-) family life cycle_empty nest or single parents or solitary household (-), spending behaviour_exceed (+),	3974	households	U.S.	Cross-sectional	Double-hurdle model

Avery, Calem & Canner (2004)	Probability of default	unemployment rate, marital status, credit score, age, age of account, census track's income (where the applicant resides), credit type (revolving installment, mortgage, credit line)	unemployment rate (+), marital status_long term married (-), marital status_new divorced (+), credit score (-), age_unknown (+), census track's median income (-), credit type_mortgage (-)	122.656	Secondary data from Credit Reporting agency files	U.S.	Longtitudinal	Multiple regression analysis
Brown, Garino, Taylor & Price (2005)	Level of debt Growth in debt	optimistic financial expectations, age, gender, marital status, number of children, ethnicity, household size, employment status, car ownership, economic variables	optimistic financial expectations (+), value of house (-), household size (+), marital status_married (-), gender_male (-), employment status_second job (+)	2700	Households	U.K.	Longtitudinal	Random effects approach Cross section analysis
Yilmazer & DeVaney (2005)	Problematic / outstanding debt	family life cycle, financial assets, non-financial assets, age, age-squared, family income, education, marital status, gender, ethnicity, the number of children, health status, risk tolerance, employment status	age (-), financial assets (-), family income (-), education_college (-), marital status_married (+), gender_female (-), ethnicity_white (-), health status_poor (-), risk tolerance (+), employment status_self-employed (-)	4261	Households	U.S.	Cross-sectional	Multiple regression analysis
Oni, Oladele & Oyewole (2005)	Probability of default	age, education, household size, home distance from credit source, income, interest rate, loan size, marital status, occupation, financial outler, loan preference, amount end up sourcing from financial outler, gender	age (+), education (-), income (-)	100	Farmers	Nigeria	Cross-sectional	Probit regression analysis
Norvilitis et al. (2006)	Level of debt	sensation seeking, materialism, attitudes towards debt (debt tolerance), gender, GPA, number of credit cards, hours worked each week, credit card use, age, year at school, compulsive spending, delay of gratification, financial knowledge, expenditure at weekends, belief in future income, perceived financial well-being, overall stress	financial knowledge (-), number of credit cards (+), delay of gratification (+), perceived financial well-being (-), overall stress (+), projected debt repayment (+), age (+)	448	Students	U.S.	Cross-sectional (5 colleges in 3 states)	Multiple regression analysis
Stone & Maury (2006)	Indebtedness	age, parents' attitude towards credit card use, number of credit and store cards, rank (pay grade), perceived financial condition, vehicle ownership, money beliefs and behaviours (MMBS), adverse life events, financial events of respondent, financial events of parents, methods of relieving stress	adverse life events (birth of a child/adoption, relocation) (+), money beliefs and behaviours MMBS (+), methods of relieving stress (+)	438	U.S. Airforce enlisted members	U.S.	Cross-sectional	Logistic regression analysis
Troisi, Christopher & Marek (2006)	Financial behaviour_positive (attitudes towards debt)	Materialism & money spending attitudes (taxonomy of Tatzel (2002)	Value seekers (money_tight & materialism_high) (+) Non-spenders (+) Big spenders (-)	266	Adults and college students	U.S.	Cross-sectional	Multiple regression analysis

Perry (2008)	Probability of default (based on FICO score)	locus of control, financial knowledge, income, education, age adverse life events (the incidence of experienced major medical expenses, extended unemployment, a significant reduction in income in the past two years)	Financial knowledge (+), locus of control_external (-), income (+), education (+), age (+), adverse life events_medical expenses (-), adverse life events_extended unemployment (-), adverse life events_a significant reduction in income (-)	8769	Households	U.S.	Cross-sectional	Logistic regression analysis
Nelson, Lust, Story & Ehlinger (2008)	Level of debt	Gender, year at school, ethnicity, perceived stress, reported stress management, health risk factors (body mass, physical activity, sedentary behaviour, dietary patterns, weight control behaviours, body satisfaction)	Year at school (+), body mass (+), physical activity (-), sedentary behaviour (+), dietary patterns_infrequent breakfast consumption (+), weight control behaviour_unhealthy (+), body satisfaction (-)	3206	Undergraduate and graduate students at a public university	U.S.	Cross-sectional	Poisson regression analysis
Norvilitis & MacLean (2010)	Level of debt Credit misuse	credit card use, perceived financial well-being, delay of gratification, perceived financial knowledge, parent bailout, parent financial education, parent facilitation	<u>level of debt</u> Credit card problem use (+), perceived financial well-being (-), parent facilitation (-), parent bailout (-), parent instruction (+), financial knowledge (+) <u>Credit misuse</u> parent facilitation (-), parent instruction (+), parent reticence (+), delay of gratification (-), parent bailout (-)	173	College students	U.S.	Cross-sectional	Multiple regression analysis
Abdou, Pointon & El-Masry (2008)	Debt repayment behaviour	loan amount, loan duration, occupational company (public, private, multinational), branch, gender, marital status, age, salary (monthly), additional income, home ownership,home telephone, utility bill, occupation (title/position), education, number of sources of borrowing (loans from other banks), relation with other banks, credit card status, corporate guarantee, other guarantors	loan amount, occupational company (public, private, multinational), gender, marital status, age, salary (monthly), additional income, home ownership,home telephone, education, number of sources of borrowing (loans from other banks), corporate guarantee, other guarantors	581	Clients of bank	Egypt	Longtitudional	Discriminant analysis Probit regression analysis Logistic regression analysis Neural networks Probabilistic neural networks not:hepsi kullanılmış neural nets daha iyi performans
Ding, Chang & Liu (2009)	Debt repayment behaviour (intention not to pay)	Locus of control, risk-taking propensity (indirect affect), general ethical judgements about credit card utilization	<u>Intention not to repay debt</u> External locus of control (+), general ethical judgements_actively benefiting from illegal activities (+), general ethical judgements_benefiting at the expense of others (+)	448	Credit card holders (Over the age of 20)	Taiwan	Cross-sectional	Structural equation modeling

Nurcan & Bicakova (2010)	Debt repayment behaviour	Self-control (composite variable/no budget, lack of money education, poor shopping habits, bank account problems) adverse life events (unemployment, change in employment, failed business, partner not working, temporary layoff/strike) adverse life events (injury/illness, caring for relative/friends, death in the family), adverse life events (preganacy/childbirth), adverse life events (reduced income, lost part time income, reduced benefits, reducation in hours/overtime, salary fluctuates/commission), adverse life events (seperation/divorce), smoking, age, gender, employment status, income, expenditure, number of dependents	age (+), gender (+), employment status_self employed (-), self-control (-), adverse life events (-), number of depdendents (+),	60.495	Secondary data from Consumer Credit Councelling Service (CCCS) clients at a Debt Management Plan (DMP) program	U.K.	Longtitudional	Cox regression analysis
Rutherford & DeVaney (2009)	Credit misuse	attitudes towards credit (good, ambivalent, bad), risk tolerance, time horizon, specific attitudes towards credit, age, source of financial credit advice, level of shopping, payment pattern, education, income	Attitudes towards credit_good (+), risk tolerance_no tolerance for risk (+), time horizon (-), specific attitudes towards credit (+), age (-), source of financial credit advice_media (+), level of shopping, payment pattern_behind schedule (+), education_college (-),	3476	Households	U.S.	Cross-sectional	Logistic regression analysis
Wang & Xiao (2009)	Indebtedness	Compulsive buying, social support for debt, impulse buying, income pattern_budget constraint, family income, gender	Compulsive buying (+), social support for debt (-), income pattern_budget constraint (+)	272	College students	U.S.	Cross-sectional	Logistic regression analysis
Fogel & Schneider (2009)	Credit misuse	income, employment status	income (+), employment status_full time (+)	301	College students	U.S.	Cross-sectional	Analysis of variance (ANOVA) models ANCOVA
Berg, Sanem, Lust, Ahluwalia, Kirch & An (2010)	Level of debt	Smoking, drinking, high-risk drinking, physical activity, mental health, age, gender, type of school	Smoking (+), drinking (+), high-risk drinking (+), physical activity (-), mental health (-), age (+), gender_female (+), type of school_four-year (+)	9910	Students at 14 midwestern colleges	U.S.	Cross-sectional	Logistic regression analysis

Sustersic, Mramor & Zupan (2009)	Debt repayment behaviour	age, gender, number of matured and repaid loans in the year preceding loan application,sum of principle repayments in the year preceding loan application, amount of loan, interest rate, loan maturity in months, payment method (3 variables), subsidiary (15 variables), average foreign exchange savings account balance (10 variables), average domestic currency savings account balance (10 variables), use of bank services over the phone, transaction account with the bank (7 variables), limited number of checks approved by the bank, cashflows (5 variables), use of credit card, use of automatic bank transfers, credit limit (5 variables), number of credit cards, loan approve date	loan maturity in months, subsidiary (3 variables), average foreign exchange savings account balance (1 variable), average domestic currency savings account balance (6 variables), transaction account with the bank (2 variables), limited number of checks approved by the bank, cashflows (1 variable), use of credit card, use of automatic bank transfers, credit limit (1 variable)	581	Clients of bank	Slovenia	Longtitudional	Neural networks
Bhardwaj & Bhattacharjee (2010)	Probability of default	attitudes towards money, income	attitudes towards money_power & prestige (-), attitudes towards money_anxiety (+), income (+)	501	Customers of an MNC Bank	India	Cross-sectional	Discriminant analysis
Mewse, Lea & Wrapson (2010)	Level of debt	Social identity, perceptions of financial situation, gender, age, ethnicity, education, marital status, housing tenure, employment status, family life cycle, income, total debt, number of debts, number of times court proceedings had been issued, optimism, locus of control, self-efficacy, home ownership, self-esteem, number of children	optimism (-), self-esteem (-), locus of control_internal (-), age (-), home ownership_rent (+), number of children (+), education (-), employment status_non-employed (+), frequency of seeking advice (+)	5704	General population	U.K.	Cross-sectional	Logistic regressions
Joireman, Kees & Sprott (2010)	Level of debt	Consideration of future consequences (CFC), compulsive buying (CBT)	Consideration of future consequences (CFC) (-), compulsive buying (CBT) (+)	249	College students	U.S.	Cross-sectional	Linear regression analysis
Sidoti & Devasagayam (2010)	Credit misuse	attitudes towards risk, materialim & money spending attitudes, influence of credit card vendors	attitudes towards risk (+), materialim & money spending attituds (+), influence of credit card vendors_whether a credit card accepted based on gifts (+)	335	students	U.S.	Cross-sectional	Linear regression analysis
Bryan, Taylor & Veliziotis (2010)	Indebtedness (existence of any unsecured arrears)	age, home ownership, income (household annual), region, family life cycle, education, socioeconomis status, employment status, attitudes towards debt, debt advice, gender, marital status	age (-), gender_female (+), family life cycle_number of childeren aged under 16 (+), marital status_married (-), marital status_seperated or divorced (+), employment status_unemployed (+),employment status_retired (-),	2200 individuals (1400 households)	General population (individuals & households)	Great Britain	Longtitudional	Probit regression analysis

			employment_sick/disabled (+), socioeconomic status_managerial & prof occupied (-), socioeconomic status_never worked (+), education_degree (-), home ownership_mortgage (+), home ownership_social tenant (+), home ownership_private tenant (+), region (significant)					
Ismail (2011)	Debt repayment behaviour	Amount of loan borrowed, repayment type, unemployment & income uncertainty, students' background (age, gender, ethnicity, marital status, number of dependents), institutional characteristics, academic experiences, parents' income & education, knowledge about loan agreement, awareness of education debt, perceptions towards loan repayment, attitudes towards debt, parent instruction	Parent instruction (+), attitudes towards loan repayment (+), perceptions towards loan agreement (+), perceptions that loan repayment will affect quality of life after graduation (+), awareness of loan repayment created by media (+)	640	Malaysian students in public universities (20 universities)	Malaysia	Focus groups semi-structured interviews questionnaire survey (cross-sectional) structured interviews	Structural equation modeling
Tan, Yen & Loke (2011)	Level of debt	age, gender, ethnicity, education, income, loan commitments, previous card holdings, number of bank accounts, bad debt history (existence of loan defaults past 3 years), ethnicity, number of cards, financial knowledge, household size, home ownership	age (+), loan commitments (+), number of bank accounts (+), bad debt history (+), number of credit cards (+), ethnicity_Chinese (-)	938	General population	Malaysia (3 major cities)	Cross-sectional	Probit regression analysis
Palan, Morrow, Trapp & Blackburn (2011)	Credit misuse	self-esteem, attitudes towards money_power & prestige, risk-taking	attitudes towards money_power & prestige (+)	260	College students	U.S.	Cross-sectional	Structural equation modeling
Garqarsdottir & Dittmar (2012)	Level of debt Money management skills	Materialism, money management, compulsive buying, financial worry, income, mood buying motives	Materialism (+)	191	Sample from the national register of Iceland (Over the age of 18)	Iceland	Cross-sectional	Structural equation modeling
Smith (2011)	Debt repayment behaviour	Financial literacy, family income, credit card distress, grade point average (GPA), credit card ownership, credit card balances, parents' education, ethnicity	ethnicity_African American (-), family income (-), GPA (-), financial literacy (-), parents' education (-)	330	Undergraduate college students	U.S.	Cross-sectional	Multiple regression analysis

Harrison & Chudry (2011)	Indebtedness	gender, age, ethinicty, social class, year of study, financial literacy, extraversion, neuroticism, attitudes towards debt, subjective norm_peers, subjective norm_parents/family, money management	extraversion (+), attitudes towards debt_debt resignation (+), attitudes towards debt_comfort (+), money management (-)	604	Undergraduate students	U.K.	Cross-sectional	Multiple regression analysis
Davey & George (2011)	Financial behaviour_positive financial behaviour_negative	Locus of control, conscientiousness, neuroticism, agreeableness, openness to experience, extraversion	Financial behaviour_positive Locus of control_internal (+), conscientiousness (+), agreeableness (+), openness to experience (-) neuroticism (-) Financial behaviour_negative Extraversion (+)	269	General population (ages 16-71)	NR	NR	Regression analysis
Ottaviani & Vandone (2011)	Level of debt	age, employment status, net wealth, income, number of children, gender, education, informal credit, impulsiveness,Iowa gambling task (IGT score), anticipatory SCRs disadvantageous decks	impulsiveness (+), Iowa gambling task (IGT score) (-) employment status_unemployed (+), employment status_self-employed (-), net wealth_first quartile (+), number of children (+), net wealth_third & fourth quartile (-)	445	Caucasian (investors and full time employees at international asset management societies)	Italy	Longtitudinal (2 Years)	Probit regression analysis
Wang, Lu & Malhotra (2011)	Level of debt	age, gender, income, education level, social class, profession, family life cycle credit limit, payment due date, number of credit cards, length of credit card ownership, attitudes towards money, satisfaction with life, attitudes towards credit, attitudes towards debt, attitudes towards risk, self-control, self-esteem, sensation seeking, deferring gratification, self-efficacy, locus of control, impulsiveness	gender_male (+), social class_low (+), income_ more than 1489 dolars (+), age_25-35 (+) Self-control (-), self-esteem (-), self-efficacy (-), deferring gratification (-), locus of control_internal (-), lenght of credit card ownership (-), total number of credit cards (+), credit limit_more than 1489 dolars (+), attitude towards credit_behaviour (+), attitudes towards credit_affective (-), attitudes towards credit _cognitive (-), attitudes towards money_power prestige (+), attitudes towards money_retention (-), attitudes towards debt (+)	1410	Credit card holders (Chineese comercial bank's database)	China	Cross-sectional	Stepwise regression analysis
Acquah & Addo (2011)	Debt repayment behaviour	education, length of employment, income, loan amount, loan processing procedures, age	education (+), length of employment (+), income (+), loan amount (-), age (-)	67	Fisherman	Ghana	Cross-sectional	Multiple regression analysis
Robb (2011)	Credit misuse	gender, ethnicity, year at school, parent's income, employment, whether a financial course was taken, number of debts, had other financial aid, whether the student is financially independent, financial knowledge	number of debts (+), had other financial aid (+), whether the student is financially independent (+), financial knowledge (-)	1354	College students	U.S.	Cross-sectional	Three level multinomial regression analysis

Xiao, Tang, Serido & Shim (2011)	Credit misuse Level of debt Financial behaviour_positive	Parents' socioeconomic status (father's education, mother's education, parents' income), subjective financial knowledge, objective financial knowledge, attitudes towards positive financial behaviour, parental norm, friends' norm, financial behaviour_positive, risky credit behaviour, self-efficacy, controllability	Financial behaviour_positive attitudes towards positive financial behaviour (+), self-efficacy (+), controllability (+), parental norm (+) credit misuse financial behaviour_positive (-), objective financial knowledge (-) Level of debt (outstanding) risky credit behaviour (+), parents' socioeconomic status (father's education, mother's education, parents' income) (-), subjective financial knowledge (+), objective financial knowledge (+), financial behaviour_positive (-)	1242	College students	U.S.	Cross-sectional	Structural equation modeling
Wang, Lv & Jiang (2011)	Debt repayment behaviour_positive	attitudes towards money (power-prestige, retention, distrust, anxiety), satisfaction with life, attitudes towards credit (affective, cognitive, behaviour), attitudes towards debt, attitudes towads risk (benefit-risk balance, curiosity,risk endurance)	attitudes towards money_power-prestige (+), attitudes towards money_retention (-), attitudes towards credit_behaviour (+), attitudes towards credit_affective (+), attitudes towards credit_cognitive (-), attitude towards debt_positive (+)	537	corporate personnel & students (under the age of 35)	China	Cross-sectional	Stepwise regression analysis
Brougham, Jacobs-Lawson, Hershey & Trujillo (2011)	Debt repayment behaviour_negative	gender, financial anxiety (anxiety about meeting financial obligations), money management, financial behaviour_positive (responsibility), financial knowledge, introversion, emotional stability, materialism, future time persepective	emotional stability (-), materialism (+), financial behaviour_positive (responsibility) (-)	628	students	U.S.	Cross-sectional	Ordinary least squares regression analysis
Berneth, Taylor, Walker & Whitman (2012)	Probability of default (based on FICO score)	neuroticism, conscientiousness, agreeableness, extraversion, job performance (task performance, organizational citizenship behaviour, workplace deviance), education	conscientiousness (-), agreeableness (+), job performance_task performance (+), job performance_organizational citizenship behaviour (+), education (+)	142	employees, alumni and students at a university	U.S.	Cross-sectional	Multiple regression analysis
Santiago, Wadsworth & Stump (2011)	Probability of delinqency	Socioeconomic status (SES/income, parental education, employment status), income, neighbourhood disadvantage, poverty-related stress, age	Povery-related stress (+), socioeconomic status (+), neighbourhood disadvantage (+)	300	Low-income multiethnic sample	U.S.	Longtitudional	Ordinary least squares regression analysis
Gathergood (2012)	Indebtedness	age, gender, marital status, education leaving age, employment status, number of children, home ownership, household finances (income, liquid savings, unsecured debt, house	impulsiveness (+),financial knowledge (-), age 18-25 (-), employment status_unemployed (+), employment status_spouse employed (-), number of children (+)	1234	Households	U.K.	Cross-sectional	Probit regression analysis

		value, mortgage debt), consumer credit holdings (credit card, overdraft, personal loan, store card, car loan, mail order catalogue, hire purchase, home credit, pay day loan, credit union), impulsiveness,financial knowledge						
Brown, Garino, Taylor & Price (2005)	Level of debt	Attitudes towards risk_risk aversion	Attitudes towards risk_risk aversion (-)	19966	Households	U.S.	Longtitudinal	Tobit regression analysis
Donnelly, Iyer & Howell (2012) Study 1	Financial behaviour_positive (sense of financial reponsibility)	age, gender, education, extraversion, neuroticism, openness to experience, conscientiousness, agreeableness	education (+), extraversion (-), neuroticism (-), conscientiousness (+)	936	general population	U.S.	Longtitudinal	Two-step hierarchical regression analysis
Donnelly, Iyer & Howell (2012) Study 2	Financial behaviour_positive (sense of financial reponsibility) Level of debt	extraversion, neuroticism, openness to experience, conscientiousness, agreeableness, materialism, compulsive buying	Financial behaviour_positive (sense of financial reponsibility) conscientiousness (+), materialism (-), agreeableness (+) Level of debt (debt accumulation) money management (-)	993	Students	U.S.	Longtitudinal	Two-step hierarchical regression analysis
Costa (2012)	Probability of default	income (total household income), mortgage existence,expenditure, assets, amount of debt, wealth, household status (one adult, several edults, one adult and children, several adults and children), age, education, employment status, adverse life events (4 variables regarding the change in financial situation such as job loss)	income (-), expenditure (+), amount of debt (+), wealth (-), household status (one adult, several edults, one adult and children, several adults and children)_with children (+), education (-), employment status_unemployed (+), adverse life events (+)	1619	households	Portugal	Cross-sectional	Logistic regression analysis
Meng, Hoang & Siriwardana (2013)	Level of debt	interest rate, unemployment rate, inflation, consumer price index (CPI), number of new dwellings, inflation, housing debt, GDP, population	interest rate (-), unemployment rate (-), number of new dwellings (-), inflation (-), GDP (+), population (+)	NA	Households	Australia	Longtitudinal	Cointegrated vector autoregression (CVAR) model
Stumm, O'Creevy & Furnham (2013)	Financial behaviour_negative (Probability of experiencing adverse financial events) such as bankruptcy	education, income, financial behaviour_positive (financial capabilities of making ends meet, keeping track, planning ahead, staying informed), attitudes towards money (power, security, generocity, autonomy)	education (-), income (-), financial behaviour_positive_making ends meet (-), financial behaviour_positive_keeping track (+), financial behaviour_positive_planning ahead (+), financial behaviour positive staying informed (-), attitudes towards money_power (+), attitudes towards money_security (-)	109472	General population	U.K.	Cross-sectional	Logistic regression analysis

Nepomuceno & Laroche (2013)	Level of debt	materialism (happiness, success, centrality), anti-consumption life style (frugality, tightwadism, voluntary simplicity)	Level of debt anti-consumption life style_voluntary simplicity (-), materialism_happiness (+), materialism_success (-)	502	customers of a specific bank	Brasil	Cross-sectional	Hierarchical regression analysis
Cubiles-de-la-Vega, Blanco-Oliver, Pino-Mejias, Lara-Rubio (2013)	Probability of default	8 financial ratios, 9 macroeconomic indicators, 22 non-financial information	13 significant variables in logistic regression 18 significant variables in linear discriminant analysis	5451	Microenterprise owners	Peru	Longtitudinal	Neural networks
Limerick & Peltier (2014)	Level of debt	debt attitudes and behaviour_debt management skills, locus of control, impulsiveness, materialism, anxiety on financial matters, gender, age	debt attitudes and behaviour_poor debt management skills (+), locus of control_external (+), impulsiveness (+), materialism(+), anxiety on financial matters (+)	322	Students	U.S.	Cross-sectional	Multiple regression analysis
Yang & Lester (2014)	Level of debt Probabilty of default	openness to experince, neuroticism, conscientiousness, agreeableness, extraversion, IQ Score	level of debt Extraversion (-), agreeableness (-), conscientiousness (-), openness to experience (+) probability of default openness to experience (+), IQ score (-)	619397	Secondary data from inventory of Rentfrow et al. (2008) & Credit Bureau Secondary data on IQ Scores (McDaniel, 2006)	U.S.	Longtitudional	Multiple regression analysis
Rogers, Rogers & Securato (2015)	Probability of default	age, gender, state of origin, education, marital status, home ownership, spouse's education, household size, occuation of the spouse, income, income of spouse, family income, number of vehicles owned, estimated values of vehicles stated, number of properties, estimated value of properties, existence of financial investments, number of credit cards, adverse life events, number of dependents, type of property, time at the residence, occupation, length of employment, attitudes towards money_meaning of money, compulsive buying, drinking, social comparison, financial education, consumer behaviour, optimism, self-efficacy, locus of control	Self-efficacy (+), attitudes towards money_meaning of money_suffering (+), attitudes towards money_meaning of money_inequality(+), attitudes towards money_meaning of money_conflict (+), compulsive buying (+), drinking (+), consumer behaviour_necessity (+), income of spouse (-), family income (-), marital status_consensual union (+), home ownership_rent (+), spouse's education_incomplete high school (+), number of credit cards (+), adverse life events (+)	847	General population	Uberlandia, Minas Gerais/Brazil	Cross-sectional	Logistic regression analysis

Kocenda & Vojtek (2011)	Probability of default	education, marital status, length of employment, sector of employment, gender, age, employment status, number of employments, occupation, expenditures/income, region loan amount, purpose of loan, length of the relationship with the bank, date of account opening, deposit behavior, type of product, number of cosigners, date of loan	education (-), marital status_married (-), loan amounth (+), purpose of loan_renovation (+), length of the relationship with the bank (-),	3403	Retail loan banking customers	Czech Republic	Longtitudional	Logistic regression analysis CARTs
Brown & Taylor (2014)	Problematic debt	openness to experince, neuroticism, conscientiousness, agreeableness, extraversion,gender, age, ethnicity, marital status, labour force status, education, self-assessed health status, income, number of children, household size, housing tenure	age (-), education (-), self-assessed health status (-), income (+), extraversion (+), openness to experience (+)	10000	Households	U.K.	Longtitudional	Quantile regression analysis
Wang, Malhotra & Lu (2014)	Problematic debt	credit limit, gender, length of credit card ownership, credit card expenditure, amount of debt, age, credit score, duration of deferred payment	credit limit (+), gender_male (-), age (-), length of credit card ownership (+), credit card expenditure (+), amount of debt (+)	1270	Secondary data from a Chinese commercial bank (behavioral data)	China	4 seasons of data	Linear regression analysis Probit regression analysis
Pirog & Roberts (2007)	Credit misuse	emotional instability, introversion /extraversion, materialism, the need for arousal, impulsiveness, body focus, conscientiousness, openness to experience, agreeableness, income, gender, age	emotional instability (+), introversion (+), materialism (+), the need for arousal (+), impulsiveness (+)	254	College students from 2 private universities	U.S.	Cross-sectional	Mediated regression analysis
Chen & Wiederspan (2014)	Problematic debt	age, gender, family income, GPA, field of study, time to degree, institutional characteristics (public, private, selectivity, size, average ratio between institutional grants and tuitiona revenue), state finance policies	gender_female (+), family income_high (-), ethnicity_black (+), GPA_highest quartile (-), field of study_business (+), field of study_health (+), institutional characteristics_public (+)	5290	College students	U.S.	Longtitudinal	Zero-one inflated beta regression
Norvilitis (2014)	Level of debt	number of credit cards, income, attitudes towards debt, financial well-being, delay of gratification	number of credit cards (+), income (+), financial well-being (-), delay of gratification (-)	855	Students	U.S.	Longtitudinal	Correlation analysis Covariance analysis

Omar, Rahim, Wel & Alam (2014)	Credit misuse	self-esteem, materialism, impulsiveness, bugdet constraint, compulsive buying	self-esteem (-), compulsive buying (+)	186	credit card user of working adults	Malaysia	Cross-sectional	Structural equation modeling
Achtziger et al. (2015)	Level of debt	Self-control, compulsive buying, gender, age, household income	self-control (-), compulsive buying (+)	946	General population	Germany	Cross-sectional	Moderated mediation analysis
Griffin & Husted (2015)	Debt repayment behaviour	social sanctions, social relations, financial capital	social sanctions (-), social relations (+)	182	Microfinance group loan users	Mexico	Cross-sectional	Structural equation modeling
Akben Selçuk (2015)	Financial behaviour_positive (paying on time, having a budget in place, saving for future)	financial literacy, parent instruction, attitudes towards money, gender, whether financial course was taken, students'class rank, work experience	financial literacy (+), parent instruction (+), gender_female (+), attitudes towards money (+), whether financial course was taken (+)	1539	college students	Turkey	Cross-sectional	Logistic regression analysis
Dahiya, Handa & Singh (2015)	Probability of default	loan duration, credit history, purpose of loan, loan amount, savings status, employment status, installment commitment, other parties, housing tenure, property magnitude, age, other payment plans, home ownership, existing credits, occupation, number of dependents, telephone ownership	loan duration, credit history, purpose of loan, loan amount, savings status, employment status, installment commitment, property magnitude, age, other payment plans, existing credits, housing tenure	1000	Credit users	Germany	Longtitudional	Ensemble learning: Neural networks C5.1 CARTs QUEST CHAID Linear regression analysis Support vector machines
Masyutin (2015)	Probability of default	age, gender, marital status, number of days since last visit, number of subscriptions, number of days since the first post, number of user's posts with photos, number of user's posts with video, number of children, major things in life, major qualities in people	age, gender, marital status, number of days since last visit, number of subscriptions, number of days since the first post, number of user's posts with photos, number of user's posts with video, number of children, major things in life, major qualities in people	27540	Social network profiles (Vkontakte-Russian social network)	Russia	Longtitudional	Logistic regression analysis
Vieira, de Oliveira and Kunkel (2016)	Financial behaviour_positive (credit card responsible use) Level of debt	Compulsive buying, materialism, credit card debt, financial behaviour_positive (credit card responsible use), ill-being perception	<u>Financial behaviour_positive</u> Compulsive buying (-), materialism (-), credit card debt (-), ill-being perception (+) <u>Level of debt</u> Financial behaviour_positive (credit card responsible use) (-), ill-being perception (-), compulsive buying (+)	1538	General population	Brasil (3 different regions)	Cross-sectional	Structural equation modeling
Hojman, Miranda & Ruiz-Tagle (2016)	Indebtedness	depressive symptoms score	depressive symptoms score (+)	10.900	households	Chilean	Longtitudinal	Ordinary least squares regression analysis

Norvilitis & Batt (2016)	Level of debt	locus of control, delay of gratificaiton, financial social comparison, parent instruction, attitudes towards credit, year at school	year at school (+), attitudes towards credit_loan resignation (+), attitudes towards credit_loan initiative (+), delay of gratificaiton (+), financial social comparison (+)	189	College students	U.S.	Cross-sectional	Multiple regression analysis
Kübilay & Bayrakdaroğlu (2016)	Financial behaviour_negative (financial risk tolerance)	openness to experince, neuroticism, conscientiousness, agreeableness, extraversion	extravertion (+), agreeableness (-), conscientiousness (-), neuroticism (+), openness to experience (+)	536	Investors live in İstanbul	Turkey	Cross-sectional	Logictic regression analysis
Zainol et al. (2016)	Indebtedness	extraversion, neuroticism, impulsiveness, purchasing for lifestyle, parental guidance, religious practice, religious principle, financial literacy	extraversion, neuroticism, impulsiveness, purchasing for lifestyle, parental guidance, religious practice, religious principle (significant)	350	Muslims having debt problems (25-45 ages)	Malaysia	Cross-sectional	Discriminant analysis
Tang & Baker (2016)	Level of debt	Self-esteem, financial knowledge	self-esteem (-)	5693	Secondary data from U.S. Bureau of Labor Statistics	U.S.	Longtitudinal	Multiple regression analysis
Limbu (2016)	Credit misuse	credit card knowledge, social motivation, credit card self-efficacy	credit card knowledge (-), social motivation (-)	427	college students	U.S.	Cross-sectional	Structural equation modeling
Ge, Feng, Gu & Zhang (2017)	Probability of default	loan amount, interest rate, loan duration, age, gender, education, marital status, verification checks (image, education, phone, identity), disclosure of social media account, number of messages, number of followers, number of friends, number of fans	loan amount (-), interest rate (+), loan duration (+), age (-), gender_female (-), education (-), verification checks (-), disclosure of social media account (-), number of messages (-), number of followers (-), number of friends (-), number of fans (-)	35457	Online loan applicants	China	Longtitudinal	Logistic regression analysis
Abdou, Tsafack, Ntim & Baker (2016)	Probability of default	loan amount, purpose of loan, loan duration, age, marital status, gender, number of dependents, occupation, education, home ownership, telephone, income, expenditure, guarantees, car ownership, accounts' functioning, existing credits, previous occupation (exceeding one year)	previous occupation_yes (-), accounts' functioning_mostly in credit (-), guarantees_yes (-), existing credits (+), expenditure (+)	599	Clients of a bank	Cameroon	Cross-sectional	Neural networks
Zhang, Jia, Diao, Hai & Li (2016)	Probability of default	age, gender, loan amount, interest rate, duration, credit score, number of successful applications, number of failed applications, social network membership score, social network prestige, social network forum currency, social network contribution, social network group	age, gender, loan amount, interest rate, duration, credit score, number of successful applications, number of failed applications, social network membership score, social network prestige, social network forum currency, social network contribution, social network group	20000	Online loan applicants	China	Longtitudinal	Decision trees

Guo et al. (2016)	Probability of default	Demographic; screen name, gender, age, verification, education, location, occupation, registration time, active level Tweet features; duplicative behaviour, retweet behaviour, usage of emoticon and mention, posting time, sentiment vocabulary, sentiment polarity Network features; number of followers, number of friends, fraction of followers that are also followees, fraction of followees that are also followers, fraction between number of followers and followees, aggregated features, centrality features High level features; Features derived from ngram features (Features derived from ngram features using Logistic Regression, using Naive Bayes, using Logistic Regression), Features derived from topic distributions (Features derived from topic distributions using Naive Bayes, using Decision Tree), Feutures derived from low-level fetures (Features derived from demographic features with different classifiers, Features derived from tweet features with different classifiers, Features derived from network features with different classifiers)	Demographic; gender, age, education, location, occupation, registration time, active level Tweet features; retweet behaviour, usage of emoticon and mention, posting time Network features; number of followers, number of friends, fraction of followers that are also followees, fraction of followees that are also followers, fraction between number of followers and followees High level features; Features derived from ngram features (Features derived from ngram features using Logistic Regression, using Naive Bayes, using Logistic Regression), Features derived from topic distributions (Features derived from topic distributions using Naive Bayes, using Decision Tree), Features derived from low-level fetures (Features derived from demographic features with different classifiers, Features derived from tweet features with different classifiers, Features derived from network features with different classifiers)	30337	Profiles of a social network (Weibo)	China	Longtitudinal	Ensemble learning; Decision trees Naïve bayes Logistic regression analysis Support vector machines Gradient boosting decision tree
Strömback et al. (2017)	Financial behaviour_positive	self-control, optimism, deliberative thinking, income, age, gender, education, financial literacy	self-control (+), optimism (+), deliberative thinking (+), income (+), financial literacy (+), age (+), gender_female (+)	2063	General population	Sweden	Cross-sectional	Ordinary least squares regression analysis
Ganzach & Amar (2017) Study 1	Debt repayment behaviour_negative	intelligence, availability of financial resources _net worth, income, parents' income	Debt repayment behaviour_negative intelligence (-), financial resources_net worth (-), income (-), parents' income (-)	12686	general population	U.S.	Longtitudinal	Logistic regression analysis

Ganzach & Amar (2017) Study 2	Debt repayment behaviour_negative	intelligence, availability of financial resources _net worth, income, parents' income, openness to experience, conscientiousness, neuroticism, agreeableness, extraversion	Debt repayment behaviour_negative intelligence (-), financial resources_net worth (-), financial income (-), parents' income (-), conscientiousness (-), neuroticism (+)	8804	general population	U.S.	Longtitudinal	Logistic regression analysis
Björkegren & Grissen (2017)	Probability of default	age, gender, loan term, loan amount, credit bureau data, mobile phone usage variables (slope of daily calls sent, the number of important geographical location clusters, SMS by day, ratio of magnitudes of first fundamental frequency to all others, correlation in SMS two months ago and duration today, difference between 80th and 50th quantile of SMS use on days SMS is used)	slope of daily calls sent, the number of important geographical location clusters, SMS by day, ratio of magnitudes of first fundamental frequency to all others, correlation in SMS two months ago and duration today, difference between 80th and 50th quantile of SMS use on days SMS is used	7068	general population (mobile phone users)	A South American Country	Longtitudional	Logistic regression analysis Random forests
Huo, Chen & Chen (2017)	Probability of default	IS converged with other service, amount of payment arrearage, number of intranet communicational friends, IS real-name registered, online duration, number of outer communicational friends, IS bound with bankcards, accumulative days of communication, accumulation of used data, IS an attractive number, times of accumulative calls, monthly average of the on-bill amounts, IS registered to APP's, monthly average of arrearages, monthly average of payments, IS a grouped number, accumulative call duration, accumulation of overdue payment arrearages, on/off line, times of being suspended, times of international roaming, times of payment arrearage, total number of communicational friends	On/off line , times of payment arrearage, amount of payment arrearage, online duration, accumulative days of communication	4518	Customers of China Unicom	China	Longtitudional	Neural networks Logistic regression analysis

Jiang, Wang, Wang & Ding (2018)	Probability of default	age, gender, occupation, length of employment, education, marital status, province, home ownership status, income, guarantor, existence of insurance, existing credits' repayment status, number of failed bids, credit limit, existence of credit score, loan amount, loan duration, application's descriptive text provided by borrower (features extracted from text)	length of employment, education, province, home ownership status, income, existence of insurance, existing credits' repayment status, loan amount, loan duration, application's descriptive text provided by borrower (features extracted from text) (significant)	39538	Online loan applicants (P2P lending platform)	China	Longtitudinal	Ensemble learning: Logistic regression analysis Naive bayes Support vector machines Random forests
Netzer, Lemaire & Herzenstein (2018)	Probability of default	loan amount, credit score, debt / income ratio, home ownership, gender, age , ethnicity, geographical location, interest rate,	word usage and writing styles (significant)	19446	Online loan applicants	U.S.	Longtitudinal	Ensemble learning: Logistic regression analysis Random forests Extra trees

RESUME

Research assistant with three years of experience in Management Information Systems department, and currently candidate of PhD degree in Management Information Systems. Completed bachelor's degree in Electrical & Electronics Engineering at Bilkent University, and achieved MSc degree in Engineering Projects & Systems Management in Kingston University with distinction degree. Completed project proposals for four projects which focused on the development of decision support systems and business models. Extensively studied on the topics of decision support systems, project management, ICT adoption, ICT literacy, information systems and system complexity.