Better member outcomes in superannuation through data driven financial literacy prediction

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I, Ben Culbert declare that this thesis, submitted in fulfilment of the requirements for the award of Doctorate in Analytics, in the School of Computer Science, Faculty of Engineering and IT at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This thesis has not been submitted for qualifications at any other academic institution. This research is supported by an Australian Government Research Training Program Scholarship.

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Abstract

Through a combination of product innovation and government reform the retirement savings system in Australia has become increasingly complex. Everyday Australians are now required to possess sophisticated financial decision making skills in order to safely navigate the many risks and opportunity costs associated with their superannuation. The decisions that savers make regarding their investments will have a significant impact on their retirement wellbeing. As a result, it is paramount for any responsible financial institution to actively measure, monitor and elevate the financial literacy of its members. To date, there is no research which proposes a suitable context specific construct for financial literacy in superannuation which is predictive of financial outcomes and utilises passive administrative data to enable ongoing measurement. To address these challenges this research first proposes a measurement construct for financial literacy in superannuation informed by the results of a financial literacy survey enriched with administrative member data. Next, I propose a novel solution for the prediction of superannuation literacy using a vast dataset of demographic and behavioural features. The prediction framework addresses the issue of non-response bias while maximising predictive performance. Finally, the prediction framework is validated against a real world business problem, customer churn. The findings of this research indicate that the measurement construct for superannuation literacy significantly outperforms the conventional measure against a number of financial outcomes. Superannuation literacy outperforms common financial literacy by a multiple of 7.1, 11.2 and 8.9 for account balance, portfolio return and portfolio volatility respectively. The prediction framework for superannuation literacy outperforms a number of state of the art algorithms for prediction. The aggregate measure for superannuation literacy achieves an R square of 84.6% and is highly correlated to positive financial outcomes in super. Validation against customer churn provides an insight into the complex relationship between financial sophistication and decision making. This research provides the framework and tools to monitor and engage superannuation members based on their sophistication and intervene where they are determined to be at-risk, requiring additional support to manage their retirement savings, or to maximise member satisfaction and engagement.

Keywords – Financial literacy, superannuation, passive system, outcomes-based measurement

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1. Introduction

Since 1991 Australian employers have been required by law to contribute as a percent of income to the retirement savings of all employees. For this reason, the superannuation industry is very unique; participation is obligatory, short term gains cannot be realised and withdrawals from the system are typically not allowed until retirement. This means that the entire Australian workforce are investors in the often complex assets sold by super funds.

In the years to come government funding for retirement will progressively diminish and Australian's will increasingly rely on superannuation savings during retirement. The decisions that Australians make with respect to their superannuation and retirement planning will have substantial consequences for their ability to live comfortably during retirement.

Financial literacy is the concept that describes an individual's 'ability to make informed judgements and to take effective decisions regarding the use and management of money (Gerrans, Clark-Murphy & Truscott 2009, p. 420)'. In the context of superannuation, financial literacy has far-reaching implications for the well-being of the Australian population and their ability to maximise the effectiveness of investment choice and retirement planning. Van Rooij, Lusardi and Alessie (2011) propose that the failure of some individuals to plan for their retirement is predicated upon a lack of financial literacy.

In order to maximise the financial well-being of all Australians it is important to first clearly define financial literacy from the perspective of the superannuation industry and its participants. While a substantial body of research exists around financial literacy many researchers have failed clearly distinguish between financial knowledge and financial literacy. Furthermore, no study has been conducted which clearly links a suitable definition for financial literacy with retirement outcomes. Additional work is required to first develop a suitable definition for financial literacy which takes into account the complex processes required for financial decision making.

1.1. Motivation

This thesis is motivated by the thesis that there is a current need to measure financial literacy which addresses the current challenges associated with the real-world implementation of a literacy monitoring framework for superannuation. This thesis puts forward that these challenges can be addressed through the application of advanced machine learning processes to passive client data.

This thesis demonstrates that a measure for financial literacy ought to be derived with a view of financial outcomes and built on passive administrative data, discarding long held conventions relying on test-based measures and paving the way for the ongoing measurement and intervention of financial literacy in superannuation. This research provides evidence highlighting the importance of defining and measuring financial literacy within superannuation and discusses how past research has fallen short of developing an effective passive measurement for financial literacy.

Financial literacy is the term used to describe the capacity of individuals to make sound financial decisions in order to maximise their financial well-being. As such, financial literacy encompasses all processes influencing the decision making process. The Organisation for Economic Cooperation and Development (OECD) provides guidelines around the definition for financial literacy and states that it includes three key areas; financial knowledge, financial behaviour and financial attitude (OECD, 2013).

Superannuation is the mandatory national savings system for retirement in Australia. Due to the obligatory nature of superannuation, it represents the largest and most unbiased cross-section of the Australian population’s financial habits. As a result, financial literacy within superannuation is of keen interest to policy makers and wealth management businesses who share an interest in the well-being of Australians during retirement (Gerrans, Clark-Murphy & Truscott 2009).

An *outcomes-based measurement* for financial literacy focuses on the effectiveness of individuals in maximising their retirement savings through superior decision-making. This is in stark contrast to past research, which commonly uses the responses of financial knowledge questionnaires to measure financial literacy.

A *passive system* for the measurement of financial literacy operates without the input of an external party. To illustrate this concept, existing approaches rely heavily on the participation of survey recipients in order to measure financial literacy. This process is not a passive strategy since it requires participation from external agents. A passive strategy utilises pre-existing datasets within financial institutions for the measurement of financial literacy. This strategy addresses the high costs and biases introduced through customer surveys.

1.2. Stakeholders, Aims, Objectives, and Significance

1.2.1. Stakeholders

Stakeholders to this research include all those who have an in the measurement and management of financial literacy within superannuation in Australia and may be motivated by financial, social, economic and academic outcomes. In particular, financial institutions, financial advice professionals and certain government bodies will benefit from this research.

The primary stakeholders to this research are industry and retail super funds and their vertically integrated financial advice networks. Identification of individual financial literacy levels within superannuation offers service providers the opportunity to engage super members on a one-to-one basis. This research will provide the framework to institute numerous initiatives within superannuation funds including but not limited to; customer protection, advocacy and enablement, product and service innovation, targeted interventions and marketing, educational programs and retirement planning, tailored financial advice and risk monitoring.

The Australian Securities and Investments Commission (ASIC) is responsible for the articulation and delivery of the National Financial Literacy Strategy. More broadly, ASIC is the responsible government entity charged with promoting investor and consumer confidence and ensuring fair and efficient markets.

Financial Literacy Australia is a not-for-profit organisation charged with responsibility for advancing the National Financial Literacy Strategy. The organisation provides grants for research and education programmes aimed at enhancing financial literacy within Australia.

This research also has significance for academic research professionals with a demonstrated history of advancing financial literacy. Academic stakeholders with a particular interest in retirement savings, financial sophistication, financial decision making, and public policy will have an interest in the findings of this thesis. As an example, Professor AnnaMaria Lusardi is the foremost researcher for financial literacy. She is the Denit Trust Distinguished Scholar and Professor of Economics and Accountancy at the George Washington University School of Business and Academic Director of the Global Financial Literacy Excellence Centre. Professor Lusardi's research relies heavily on the active measurement of financial literacy through financial knowledge surveys and employs econometric techniques for the analysis of results. This research considers these findings and presents an alternative approach utilising machine-learning methodologies.

1.2.2. Aims

All stakeholder groups have a vested interest in the advancement of financial literacy research in Australia. In particular, the primary stakeholders to financial literacy have the following aims:

i) The aim of superannuation funds is to maximise member wealth and operational revenue. Enhanced financial literacy and customer outcomes drive increased acquisition, reduced attrition and greater levels of superannuation contributions. As financially literate investors engage more in retirement planning, take advantage of tax effective superannuation contributions, and make less capital diminishing mistakes, total funds under management (through which revenue is derived) increases.

ii) The aim of the Australian government is to increase social welfare and minimise net payments through the aged pension. Through heightened financial literacy, investors are expected to accumulate more wealth (Clarke, Lusardi & Mitchell, 2014a; Chu et. al., 2017). Greater wealth means more Australians will be able to enjoy a comfortable lifestyle during retirement through self-funding.

iii) The aim of academic stakeholders is to address the current gaps in financial literacy research. Past research has been challenged to develop a measurement construct in line with the accepted definition for financial literacy. Important factors guiding the decision making process, such as financial behaviour and attitude, are unobservable through conventional approaches. Furthermore, research has failed to clearly articulate the relationship between retirement outcomes and financial literacy. Finally, the conventional approach to financial literacy measurement relies on the results of voluntary customers surveys. This approach is expensive, timely, provides limited insight and is inherently biased. Research has fallen short in addressing these issues due to the vast amount of administrative data required and the complexity of financial decision making.

1.2.3. Objectives

The primary objective of this research is to deliver an advanced procedure for the measurement of financial literacy in superannuation through the application of machine learning methodologies to passive customer demographic and behavioural data. The benchmark for success for this deliverable is that the model is predictive and outperforms the conventional test-based measure for financial literacy. Model evaluation metrics such as F1-score, gini coefficient, recall, accuracy and mean absolute error (MSE) will be used to assess the predictive power of the model. Successful implementation will identify superannuation customers and appropriately segment based on financial sophistication and financial outcomes. Comparative analysis will also yield insight into the effectiveness of this novel approach to financial literacy measurement. Estimates of financial literacy using conventional approaches will be compared to the outcomes-based machine-learning model to provide conclusions regarding the contributions of this research.

1.2.4. Significance

Financial literacy in superannuation is relevant to all Australians. Over 90% of working Australian's hold retirement savings through superannuation. As a result, it is important that all Australians have the skills necessary to make sound financial decisions for their retirement.

In addition, research indicates that individuals with greater financial knowledge (a component of financial literacy) earn more in risky markets, they seek out expert advice and they are better at managing their finances and planning for retirement (Lusardi & Mitchell, 2014a; Chu et. al., 2017; Lusardi & Mitchell, 2011a).

Despite the well documented advantages of financial literacy, levels in Australia remain low. Research indicates that only a small proportion of the population are able to correctly answer common financial knowledge questions (Agnew, Bateman & Thorpe, 2013). Many Australians don't understand how their superannuation is invested or recognise the decisions they must make in order to maximise their retirement savings (Lusardi & Mitchell, 2007).

As a result, there is a funding gap in Australia. The current estimate for the national retirement savings shortfall is $768bn, or $70,100 per person (Rice Warner, 2014). Research acknowledges that the current 9.5% employer contribution rate is not sufficient to provide adequate lifetime retirement savings (Rice Warner, 2014). Recently, the Australian government has tightened means-testing for the aged pension. This indicates that eligibility for the aged pension is narrowing. This trend is expected to continue. With an expected 5.5m Australians retiring between 2011 and 2030, in combination with a diminishing government safety net, more Australians will be living in poverty during retirement.

Past efforts to measure financial literacy have failed to appropriately design an acceptable measurement framework for financial literacy, and have instead relied upon numeracy surveys to explain the highly intricate process of financial decision making.

This research will provide a blueprint for financial institutions to establish a passive measurement framework for financial literacy. This research addresses the high costs, biases and low participation rates associated with customer surveying. With a greater understanding of customer financial literacy and the qualities driving better retirement outcomes, financial institutions will have a roadmap for product and service innovation. Targeted customer interventions, education and advice will drive greater engagement with superannuation, higher levels of contributions and more effective investment allocation.

For the Australian government, this research will provide guidance on what qualities drive superior retirement outcomes. Feature importance and associated evaluation metrics will illustrate the relationship between retirement wealth and specific behaviours, knowledge sets and attitudes. While a significant amount of social resources are spent on financial literacy enhancement programs in Australia, very little evidence exists to suggest that the conventional measures for financial literacy improve the financial well-being of individuals and families (Hadar, Sood & Fox, 2013). This thesis will highlight those factors that drive positive financial outcomes and compare those to conventional literacy measurements. This work will provide key insights for the prioritisation of government reform and spending.

This research also serves to fill the gaps in academic research for financial literacy. The model will be developed in line with the accepted definition of financial literacy. The model will take into account a variety of previously unobservable features representative of financial behaviours and attitudes. This approach will quantify the relationship between financial literacy and retirement outcomes. Finally, the proposed objectives will discard customer surveys, and instead develop a passive model for measuring financial literacy in a low cost, timely and efficient manner. Addressing these gaps is made possible through the combination of advanced machine learning methods and administrative data. This research utilises the largest and most diverse industry dataset ever made available for financial literacy research.

1.3. Research problems

This research confronts several research problems across financial literacy, superannuation and computer science. In particular, the following research problems are addressed;

i. How to design and validate an active measurement construct for financial literacy in superannuation using survey data. This research problem is derived from the need to define the construct which best describes the decision making abilities of individuals within the context of superannuation. Using active survey data, this questions seeks to understand how best to construct such a definition.
ii. How to establish a framework for ongoing monitoring of financial literacy in superannuation through the use of passive data. This research problem seeks to address the requirement to administer surveys to establish a value for individual financial literacy. Engagement from superannuation is well understood to be low. In order to implement a framework for financial literacy measurement and monitoring, passive administrative data must be used in place of active survey data.
iii. How to validate proposed solutions against business outcomes. Understanding the interaction between key customer metrics and financial literacy is important to instruct the development of strategic response plans and customer interventions. This research problem seeks to understand these interactions to inform industry applications for superannuation literacy.

1.4. Research contributions

This research proposes a number of novel solutions required to deliver a passive outcomes based measure for financial literacy in superannuation. In particular, this research delivers a measurement construct for financial literacy in superannuation, a prediction model for financial literacy in superannuation using passive administrative data, and a validation of the measurement and prediction framework against business outcomes and key performance indicators.

1.4.1. Financial literacy for superannuation members using survey data

Through partnership with a leading retail superannuation fund in Australia, Colonial First State, I analyse the results of a financial literacy survey issued to 12,468 superannuation members. The survey is comprised of 26 questions including one instructional manipulation check. The 26 questions are broken down into 5 categories; basic financial knowledge (4), superannuation knowledge (4), financial attitude (4), financial behaviours (4), demographics (6) and one financial knowledge self-assessment.

The results of the survey indicate that the basic financial knowledge questions, which are common among financial literacy research, do not do enough to contrast the varying capabilities of superannuation members. The superannuation knowledge questions and composite scores (basic + superannuation) provide a more granular contrast of respondents.

This research also shows that composite financial knowledge scores increase in line with positive financial attitudes and behaviours.

Comparison against past research shows that the findings are consistent with broad generalisations against demographic groups. Analysis shows that superannuation members within the test data answer the basic question set correctly at a far greater frequency than in other studies.

Finally, this study demonstrates a correlation between financial knowledge, behaviours and attitude. Further I conclude that members with greater financial literacy would enjoy greater returns at a lower level of risk, and are expected to retire with more savings.

1.4.2. A prediction model for financial literacy in superannuation utilising passive administrative data

While test based measures have become commonplace for the measurement of financial literacy this approach requires active engagement from a membership base. To support the ongoing monitoring, reporting and intervention of financial literacy a prediction model is built on passive administrative data. The data used for this task draws on the significant customer databases of Colonial First State to engineer behavioural and demographic features.

A multi-class classification algorithm will be used to build the measurement model. Classification algorithms are commonly used for prediction problems where a binary, ordinal or nominal dependent variable is specified. Label/dependent variables may have two or more unique values. Where multiple classes are specified, this is known as a multi-class classification problem.

Research into classification and regression modelling is extensive, and numerous algorithms have been identified to perform well in various scenarios. Common examples of these include Logistic Regression, Decision Tree, Naïve Bayes and K-Nearest Neighbour. Recent research points to the XG Boost algorithm (Chen, He & Benesty, 2015), a variation of gradient boosting trees, as having superior performance. In addition, the XG Boost algorithm has been identified to outperform other algorithms when tested on financial services data (Culbert et al., 2018). Importantly, adaptations of the XG Boost algorithm can be utilised for regression and classification with multiple dependent/label variables. In combination, these qualities indicate that XG Boost will perform well for this task. Additional prediction models will be used in order to contrast model performance and provide support for the champion model.

1.4.3. Validation of the prediction framework against business outcomes

Prediction scores for superannuation literacy are validated against business outcomes. I analyse literacy scores against key customer segments and performance indicators for the business to inform the development of strategic response plans and applications for superannuation literacy. I demonstrate that superannuation literacy and account attrition are intrinsically linked, and put forward solutions to address attrition using measurements of financial literacy. The findings of this research indicate that financially literate investors are more discerning with respect to the selection and management of their superannuation. As a result, exit interviews should be segmented by financial literacy in order to determine the product features that are most important to members across multiple cohorts. In doing so, superannuation finds will be able to monitor and intervene where it's determined that members may not be in a product which meets their needs or expectations.

1.5. Structure of the thesis

The remainder of this thesis contains five sections. The first section (Chapter 2) contains preliminaries and a literature review; Chapter 3 proposes a context specific measure for financial literacy in superannuation; Chapter 4 introduces a novel approach to multivariate regression to predict financial literacy maximised on financial outcomes; Chapter 5 contains an analysis of a business problem from the perspective of the proposed measure by contrasting the results of a customer churn problem with financial literacy; finally, Chapter 6 concludes with an overview of the findings, research contributions, applications for this work and recommendations for future research.

2. Preliminaries and literature review

2.1. Superannuation in Australia

Superannuation in Australia is one of the few compulsory retirement savings systems in the world (Gallery, Newton & Palm, 2011). Historically, retirement savings in Australia was a voluntary system which provided defined benefits through a consistent flow of income for policy holders during retirement. These schemes were referred to as defined benefit pensions, and since the late 1980s have closed to new members, and are now all but gone (Bateman et al., 2014). These schemes were replaced by defined contribution plans (modern superannuation funds), and participation legislated in 1992 through the Super Guarantee Act. Through defined contribution plans employers are required as stipulated by legislation to make regular contributions to eligible employees' superannuation savings at a defined rate, currently 9.5%.

In addition to the legislated employer contributions, employees have the opportunity to make additional contributions up to defined limits. Concessional contributions are made pre-tax, and charged by the fund at 15% up to $25,000 (as at 2021). Concessional contributions allow individuals to maximise their retirement savings while also reducing their total tax bill. Non-concessional contributions are post-tax contributions which have already been taxed at the marginal income tax rate. Despite non-concessional contributions being taxed at the full income tax rate, all invested funds pay a lower rate of capital gains tax than ordinary investors.

To increase competition in the industry, amendments made to the SG Act in 2005 provided employees the opportunity to exercise choice with respect to where and how their retirement savings are invested (Gallery, Newton & Palm, 2011). Investors can now choose which superannuation fund their money is invested with, and more often than not, may choose from a multitude of investment options with varying risk return profiles and investment mandates in the construction of their portfolio. Investors who either fail, or choose not to exercise choice will find themselves in a default fund. It is estimated that up to 80% of superannuation members are invested in the default fund. Increasingly, government reform has increased both the choice and risks which investors face in managing their retirement savings.

In exercising choice, investors must weigh up the investment mandates of numerous funds against their associated fees and management costs. Through ongoing government reform, risks which had previously been carried by defined benefit scheme providers now rest solely on the individual. Investment allocation, timing, longevity and liquidity risks are all carried by the investors within these funds. Further, individuals are also required to navigate the complex tax incentives associated with superannuation.

It is estimated that relying solely on employer contributions to fund retirement will provide approximately 45% of the income required (Bateman et al., 2014). As a result, there is a significant savings gaps in Australia. This is estimated to be $768bn nationally, or $70,100 per person while including provisions from the aged pension (Rice Warner, 2014).

Choices regarding the allocation of invested funds and decisions to make voluntary contributions steeply impact the expected retirement income for individuals (Bateman et al., 2014). Then it is reasonable to say that decisions made regarding the management of superannuation certainly matter, and the ability of individuals to make the sound decisions for their retirement savings will have profound consequences for their retirement well-being.

2.2. Financial literacy measurement and applications

2.2.1. Financial literacy and well-being

In recent years, financial literacy has come to the forefront for governments, economists and academics alike. In the United States the value of financial literacy and financial education programs has manifested through public policy objectives (Huston 2010). In Australia similar manifestations of public policy are evident through the creation of the Financial Literacy Foundation in 2005 (Gerrans, Clark-

Murphy & Truscott 2009). This move to improve the financial literacy of individuals and households is being driven out by governments for a number of reasons.

Generally, financial literacy is accepted to lead to improved financial well-being. This hypothesis is supported by evidence from a number of sources. Chu et al. (2017) find that individuals with a high level of financial literacy experience higher portfolio returns, and are more likely to engage the services of qualified professional consultants. Lusardi and Mitchell (2011a) find that individuals with high financial literacy show behaviours consistent with 'savvier saving and investment decisions, better debt management, more retirement planning, higher participation in the stock market, and greater wealth accumulation (p. 34)'.

In the context of government policy, the ageing population has compelled governments to establish reform in order to minimise the load on the national welfare system. This phenomenon has led to governments 'shifting responsibility to individuals to fund their own retirement (Gallery, Newton & Palm 2011, p. 4)'. To ensure that this goal is achieved it is important that individuals have adequate skills and knowledge to plan and manage their retirement savings. Retirees must therefore make careful decisions during retirement so not to outlive their savings (Chu et al. 2017).

Furthermore, research supports that where individuals and households do not participate in complex financial markets there is a sizeable opportunity loss (Van Rooij, Lusardi & Alessie 2011a). This point is especially relevant to the Australian superannuation default system. Research indicates that a large proportion of super members are disengaged and as many as 81% invested in the default fund (Gallery, Newton & Palm 2011). It is therefore likely that the apathy of these super members will be costly in the long run.

2.2.2. Defining financial literacy

Financial literacy is commonly understood to represent an individual's comprehension of the economy, financial markets and financial products. Authors who accept this definition also propose that through heightened financial knowledge individuals can enhanced their own personal financial well-being.

As found by Huston (2010) only 25% of research papers provide a concise definition for financial literacy, and commonly (more than 50%) use the terms financial knowledge and financial literacy interchangeably. Huston (2010) finds that without a concise and consistent definition for financial literacy researchers will fail to design experiments which are comparable and offer insight into the impact that results have on financial well-being. Huston (2010) offers that the definition for financial literacy needs be a construct of both financial knowledge and decision-making.

Lusardi and Mitchell (2014) propose that financial literacy must also take into account the behaviours of individuals, implying that a high level of financial knowledge does not itself indicate high financial literacy. The authors posit that further study needs to be done to understand the relationship between financial knowledge, and financial behaviours.

Potrich, Vieira and Kirch (2015) site a definition put forward by the Organisation for Economic Cooperation and Development (OECD, 2013) whereby financial literacy can be seen as ‘a combination of awareness, knowledge, skill, attitude and behaviour (p. 363)’. The authors rationalise this definition to three core areas; financial behaviour, financial knowledge and financial attitude where: financial knowledge is synonymous with comprehension of financial concepts; financial behaviour is in line with the ability to make wise financial decisions and; financial attitude is represented by the belief system of an individual and how those beliefs guide behaviour and decision making.

This paper acknowledges the definition provided by the OECD (2013) and further suggests that the definition for financial literacy is the capacity for individuals to make complex financial decisions in order to maximise their personal financial well-being. In line with the definition provided by the OECD (2013) sound financial decision making requires not only an enhanced level of financial knowledge but a set of qualities (which include behaviours and attitudes) which promote positive actions.

2.2.3. Measurement of financial literacy

Despite a diversity of definitions for financial literacy, researchers have over the past decade generally agreed upon a common approach for measuring it. Lusardi and Mitchell (2014) cite early attempts to measure financial literacy through three common financial knowledge questions shown in Figure 2.1, described colloquially as the Big Three (Hastings, Madrian & Skimmyhorn 2013). These questions seek to understand a responder's comprehension of compound interest, inflation and risk diversification. First issued in 2004 by the US Health and Retirement Study, these three questions have become the starting point for all financial literacy research (Lusardi & Mitchell 2014).

Table 2.1 Financial Literacy Questions – 2004 Health and Retirement Study (HRS)

Concept	Question	Permissible answers
Interest rates and compounding	Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years, how much do you think you would have in the account if you left the money to grow?	***More than $102*** Exactly $102 Less than $102 Don't know Refuse to respond
Inflation	Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, would you be able to buy more than today, exactly the same as today, or less than today with the money in this account?	More than today Exactly the same as today ***Less than today*** Don't know Refuse to respond
Risk diversification	Do you think that the following statement is true or false: buying a single company stock usually provides a safer return than a stock mutual fund?	True ***False*** Don't know Refuse to respond

Early work enhanced the admission of these three common questions by arguing the need to appropriately account for guessing and where respondents did not know the answer (Hill & Perdue 2008).

Building on this work Van Rooij, Lusardi and Alessie (2011a) developed a more sophisticated version of the financial knowledge survey. This survey looked to test both basic financial knowledge (which consisted of variations of the common three questions) and advanced financial knowledge. The advanced financial knowledge component of the survey tested a respondent's knowledge of bonds, mutual funds and stocks. In addition, Van Rooij, Lusardi and Alessie (2011a) sought to control for guessing by issuing multiple versions of the survey with questions reordered. The results indicated that guessing was common for the advanced financial knowledge questions.

A limitation of past efforts to measure financial literacy is that the majority of researchers fail to distinguish between literacy and knowledge (Huston 2010). As a result, surveys issued become a construct of their narrow definition of financial literacy. This can be seen to explain the prevalence of common financial knowledge questions in literacy research. A preferable approach would be to define financial literacy and explain how that definition has guided the development of the literacy survey. Because of this shortcoming, the common approach to measuring literacy through survey instead only tests it respondents' financial knowledge, and fails to understand respondents from a broader financial literacy viewpoint.

As seen in the previous section, Potrich, Vieira and Kirch (2014) take a more sophisticated view of financial literacy: encompassing financial knowledge, attitude and behaviour. As a construct of this definition, the authors administered a survey to understand not only how well respondents understood financial concepts, but also their views towards money and financial instruments, and their behaviours. A corollary to this is that the results and subsequent analysis from this survey are more sophisticated.

While the vast majority of research has measured financial knowledge as a proxy for financial literacy based through the survey responses of individuals and households, Hastings, Madrian and Skimmyhorn (2013) suggest an alternative outcomes-based approach to the measurement of financial literacy. Hastings, Madrian and Skimmyhorn (2013) suggest that a measurement construct for financial literacy based on the quality (or sophistication) of decisions would more closely align to the positive outcomes of financial literacy; financial well-being.

Such an alternative approach to measurement comes from Calvet, Campbell and Sodini (2007) where they measured the sophistication of investors based on mistakes they made. Specifically, the research classified mistakes with respect to trading errors, under-diversification and non-participation in risky asset markets. This research finds that highly sophisticated households invest more aggressively and experience higher returns.

Though the majority of financial literacy research continues to use financial knowledge as a proxy, recent studies are emerging which recognise the multi-faceted nature of financial literacy. Liu and Zhang (2021) conduct a study on risk consumer credit spending among students in China. This study demonstrates an inverse relationship in students between risky credit spending and financial literacy. The survey used to establish financial literacy levels includes not only financial knowledge, but also several questions relating to the students' borrowing behaviours and their attitudes towards debt. Similarly, Kasozi and Makina (2021) constructed a framework for financial inclusion in Uganda using a financial literacy questionnaire aimed at identifying four distinct areas described as defining financially astute investors; money management, planning ahead, financial product selection and information retrieval. Interestingly, this study has entirely discarded financial knowledge questions as part of the financial literacy construct.

Despite recent advancements, there are a limited number of examples where an outcomes-based measurement for financial literacy has been studied. Studies have in the past been limited by the heavy reliance this approach has on vast amounts of administrative data. Calvet, Campbell and Sodini (2007) used transactional level data from Sweden however many academics do not have access to the amount of data required to perform an outcomes-based research for financial literacy. Huston (2010) clearly articulates the challenges that researchers face with respect to quality data. Through this paper, Huston (2010) finds that of the 71 studies reviewed (which used a total of 52 unique datasets) the average sample size was 1,575 and ranged between

42 and 12,140. Furthermore, researchers were also challenged to generate datasets which provided a representative cross-section of society. Many of the datasets used in financial literacy research are segmented by age; where surveys were often targeted to students (secondary and tertiary).

2.2.4. Financial behaviour

Research highlights that financial literacy is correlated to optimal financial decision making. Lusardi and Mitchell (2014) find that the least financially knowledgeable interacted with financial products to their own detriment, often engaging in costly financing activities. They find that individuals with low financial knowledge often accrued large credit card debt, purchased expensive mortgages, are more likely to be victims of financial scams and fail to plan for retirement.

In addition, Van Rooij, Lusardi and Alessie (2011a) find that individuals with low levels of financial knowledge often seek information and guidance from unqualified sources, such as friends and relatives. As financial knowledge scores increase individuals more commonly consult qualified sources of information, such as financial publications.

On the other hand, Hilgert et al. (2013, as cited by Chu et al. 2017) find that individuals with high financial literacy are more likely to show positive financial behaviours such as managing personal financial commitments, financial planning, diversification and goal setting.

Research further indicates that financially literate individuals and households are far more likely to participate in the stock market (Van Rooij, Lusardi & Alessie 2011a). It is also found that individuals with higher levels of advanced literacy delegate part of the decision making process through investment in mutual funds and an advanced level of financial literacy was strongly associated with positive portfolio performance (Chu et al. 2017). This finding is supported by Van Rooij, Lusardi and Alessie (2011a) where high financial knowledge was associated with a higher likelihood for individuals to seek professional financial advice. Lusardi and Mitchell (2014) find that the financially literate are less likely to realise losses through the sale of assets which have fallen in value and more likely to make tax effective contributions to their superannuation accounts.

2.2.5. Financial attitude

Though very little research has been done to understand how the attitudes of individuals impacts financial decision making it's an important consideration and necessary to understand how decisions are made. Research conducted by Ibrahim & Alqaydi (2013) tested financial attitude through a set of survey questions aimed at understanding what level of importance respondents placed upon record keeping, managing expenses, insurance, diversification and sourcing financial information. The results of this study are extremely limited and do little to enhance knowledge around financial literacy and financial attitude. The findings conclude that there is a strong negative correlation between financial attitude and credit card borrowing.

Research conducted by Chu et al. (2017) offers a small insight into how attitude impacts upon decision making. Chu et al. (2017) create a binary 'overconfidence' measure based on how survey respondents score on a financial literacy survey. Survey respondents are asked to indicate a self-assessment of their personal financial literacy. Where respondents rate themselves subjectively as being average or above, and objectively score below average, they are labelled as overconfident. The results of this analysis are again limited however they demonstrate that where survey respondents are overconfident they are more likely to engage in risky investment behaviour.

A similar notion is proposed by Hadar, Sood and Fox (2013) who highlight a complex interaction between subjective knowledge, objective knowledge and financial decision making. Their findings suggest that enhanced subjective knowledge (or how knowledgeable individuals feel) is the strongest factor in supporting individuals to make complex financial decisions.

Paradoxically, research finds that efforts to enhance objective knowledge, through education programs, cause a deterioration in subjective knowledge and limit an individual's willingness to make financial decisions (Hadar, Sood & Fox 2013).

Through their experiment Hadar, Sood and Fox (2013) found that they could manipulate subjective knowledge through objective knowledge treatments. The findings indicate that when individuals are presented with financial concepts and material that is too complex, they are forced to re-evaluate their view of their comprehension of financial concepts. After this manipulation, individuals were less willing to act and in a simulation allocated substantially less money to risky assets (Hadar, Sood & Fox 2013). In the same experiment the opposite was also proven to be true. Where participants are presented with financial concepts that participants are able to easily grasp, subjective knowledge went up, so too participants' willingness to invest in risky financial instruments.

These findings indicate that attitude has a substantial role to play in promoting financial decision making. They also imply that any efforts to enhance financial literacy through treatments to objective knowledge, subjective knowledge or both can have potentially significant detrimental effects. The notion of overconfidence as presented Chu et al. (2017) is described as a negative outcome, where individuals show risk seeking behaviour as a result of their heightened confidence. However, Hadar, Sood and Fox (2013) explain overconfidence (which is equivalent to high subjective knowledge) as a requirement for action. As a result, education programs need to target both subjective and objective knowledge; so not to encourage high risk investment decisions, while promoting healthy financial decision making.

In the context of financial literacy, the interaction of confidence and objective knowledge add a level complexity to modelling how individuals make financial decisions. Furthermore, the findings by Hadar, Sood and Fox (2013) indicate that financial knowledge in itself is of less importance to the decision making process.

2.2.6. Explanatory variables for financial literacy

Past research on financial literacy comes to a compellingly consistent finding on the inequality of financial literacy across demographic and socio-economic groups. Understanding the context around how financial decision-making occurs is important to interpret how behaviours relate to financial literacy.

There is a substantial body of research which conclusively indicates that women, on average, score lower than men in financial literacy surveys (Agnew, Bateman & Thorp 2013; Gallery, Newton & Palm 2011; Hill & Perdue 2008; Lusardi & Mitchell 2014; Potrich, Vieira & Kirch 2015; Van Rooij, Lusardi & Alessie 2011a). Results from Van Rooij, Lusardi and Alessie (2011a) show that while women do on average have lower financial knowledge scores, they are more likely to indicate that they do not know an answer, rather than random guessing. This indicates that women may be more likely to seek professional financial advice. Chu, Wang, Xiao and Zhang (2016) find that men are more likely to engage in risky investment behaviour akin to gambling, due to overconfidence.

The age of survey respondents is also a critical factor in determining financial literacy. Van Rooij, Lusardi and Alessie (2011a) find that younger and older respondents score lowest in financial knowledge surveys. Argwal et al (2009) (as cited by Lusardi & Mitchell 2014) find that the 'elderly pay much more than the middle-aged for 10 financial products (p. 26)'.

Race is also reported to have statistically significant relationship to financial literacy. In the United States African-Americans and Hispanics suffer from lower levels of financial knowledge (Lusardi & Mitchell 2011a). While in Australia, indigenous Australians are at a disadvantage, reporting significantly lower levels of financial knowledge (Gerrans, Clark-Murphy & Truscott 2009). Past research has found non-native speakers and immigrants score more lowly in financial knowledge surveys.

Other variables identified by research include wealth, religion, education and parent education, political views, profession and dwelling type.

2.3. Machine learning techniques for measuring financial literacy

To date research has consistently failed to match the measurement of financial literacy to an appropriate measurement construct. Hastings, Madrian and Skimmyhorn (2013) suggest that a common challenge researchers face in designing experiments for financial literacy is access to the vast quantities of administrative data required to derive deeper insights and conclusions.

As a result, methodologies applied to research in financial literacy generally lack the sophistication expected for such a complex definition; derived from the beliefs, behaviours, knowledge and financial outcomes of individuals. Review of existing research indicates that the findings for financial literacy are based on descriptive statistics (Gallery, Newton & Palm 2011; Gerrans, Clark-Murphy & Truscott 2009; Hadar, Sood & Fox 2013; Hill & Perdue 2008; Lusardi & Mitchell 2011a, 2011b; Servon & Kaestner 2008), ordinary least squares regression (Agnew, Bateman & Thorp 2013; Chu et al. 2017; Ibrahim & Alqaydi 2013; Lusardi & Mitchell 2007), logistic regression (Potrich, Vieira & Kirch 2015), instrumented variables (Lusardi & Mitchell 2014), and generalized method of moments (Van Rooij, Lusardi & Alessie 2011a; Van Rooij, Lusardi & Alessie 2011b). While regression is a strong tool for economists it cannot effectively capture the complex patterns and relationships between variables where behavioural features are included.

Given that there is a lack of research supported by large quantities of administrative data there is little evidence to suggest that advanced analytical techniques have ever been applied to financial literacy study. Huang et al. (2007; 2008) have released short papers reporting improved estimation results with the application of Artificial Neural Networks and Support Vector Machines to a dataset of 17 features (survey responses). The research outcome of these papers is to report on the enhanced generalized performance of these models. While the performance is indicated to be quite high (92% ANN, 94% SVM) no further findings are put forward. As a result, these papers fail to fully to explore the potential of advanced analytical techniques in the area of financial literacy.

2.3.1. Classification and regression algorithms

Machine learning tasks typically fall into one of four learning types; supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning. Supervised learning is by far the most common class of learning tasks. Supervised learning is used where there is a known ground truth. The task then is to learn the weights associated with each of the model features which minimise the error associated with a prediction. Unsupervised learning is therefore those tasks where the ground truth is unknown and rather the task is to learn the unique interactions between unlabelled features. Unsupervised learning is common for segmentation tasks. Semi-supervised learning is a special case of supervised learning, where there are a low number of labelled records and a high number of unlabelled records. Semi-supervised learning utilises an iterative learning procedure to predict the ground truth for a small number of unlabelled records. This approach is useful in situations where it may be expensive or impractical to acquire additional labelled records. Reinforcement learning is used for highly sophisticated applications with a massive number of variables. The ground truth is rarely known and the number of inputs required for a conventional supervised learning problem are beyond the computing power of any current system. Instead, reinforcement learning uses simulation to learn how to make decision based on an understanding of the rules. Reinforcement learning has been employed for self-driving technology, natural language processing and gameplay.

The remainder of this thesis deals with supervised learning problems and therefore, this learning class will be the focus of this section.

Within the class of supervised learning, problems can be expressed as regression or classification tasks. Regression is a machine learning task which trains weights against a feature set of independent variables in order to minimise the error in explaining a continuous dependent variable. Similarly, classification seeks to employ algorithms to learn the coefficient weights which best describe the variation of a class label.

While there are a significant number of supervised learning algorithms, those provided below represent a thorough cross section of the various types of algorithms, including their strengths and weaknesses and applicability to various problems.

Ridge Regression (Tikhonov & Arsenin 1977) is a linear model with L2 regularization. L2 regularization minimizes the risk of overfitting a model by introducing a parameter for complexity, and penalizing large weights. The L2 regularization term is represented by the sum of squared weights multiplied by lambda, the regularization rate. The selected value of lambda will determine the extent to which the user favours overfitting over simplicity.

Lasso Regression (Least Absolute Shrinkage and Selection Operator) (Tibshirani 1996) is a linear model with L1 regularization. L1 regularization controls for feature sparsity, and is useful for regression problems with a large number of features. Regularization for sparsity forces low value feature weights to zero. Unlike L2 regularization, L1 is robust to outliers in a dataset, and by design is useful for feature selection.

Elastic Net (Zou & Hastie 2005) is a linear model with combined L1 and L2 regularization, offering a compromise between Ridge and Lasso.

k-Nearest Neighbours regression is a non-parametric method that does not require assumptions on the data distribution, and hence is adaptive to the data.

DTR (Decision Tree Regressor) is a popular machine learning algorithm that makes decisions based on tree structures, which mimics the decision-making mechanism used by humans.

XGB-W (XGBoost regressor within a multi-output wrapper) (Chen & Guestrin 2016) is a decision tree-based ensemble learning algorithm under the gradient boosting framework. It represents the state-of-the-art performance of supervised learning for multi-label classification and regression problems

XGB-C (XGBoost regressor within a multi-output chain) is similar to XGB-W but implemented with a multi-output chain.

2.3.2. Handling class imbalance

Class imbalance represents an issue for classification problems where the positive class of a label variable is rare. Class imbalance is problematic for machine learning tasks which assume a balanced dataset. Algorithms such as Random Forests and XG

Boost will be incentivized to treat the minority class as noise where it maximizes its performance function. This is common for machine learning tasks aimed at predicting the occurrence of rare events such as credit defaults, illness or customer churn. To handle unbalanced training data there are a number of techniques that can be employed to balance the class label. Under-sampling, over-sampling, weighted sampling and synthetic sampling are among the most common approaches.

Under-sampling involves the removal of records in the majority class in order to balance the label variable. Appropriate in instances where there is large number of records available for training, and dimensionality is not an issue. Under sampling may cause the loss of meaningful dynamics which are only captured in the deleted records.

Over-sampling involves the duplication of records in the minority class. Over-sampling is appropriate where there are a limited number of records available for training. Unlike under-sampling, over-sampling does not risk the potential loss of useful information however does pose the risk of over-fitting, and has been shown to add little value in modelling class label dynamics (Elrahman & Abraham 2013).

Weighted sampling, also known as cost sensitive learning involves the addition of a cost function to the label variable in order to penalize incorrect classification of the minority class. Where other techniques attempt to treat the imbalance through various forms of over and under-sampling, cost sensitive methods introduce a cost matrix to modify the penalty of misclassification for the minority class and are ingested by learning algorithms (He & Garcia 2009).

Synthetic minority over sampling technique (SMOTE) is an oversampling algorithm which creates additional samples of the minority class without replication by modelling the dynamics between the minority class and feature variables (Chawla et al. 2002). SMOTE is a computationally intensive task as it uses an implementation of K-NN to random select synthetic records for the minority class. Despite this, SMOTE has been shown to outperform under-sampling by AUC against the C4.5 (decision tree), Ripper and Naïve Bayes algorithms (Chawla et al. 2002).

2.3.3. Evaluation metrics

Model performance is typically assessed a number of evaluation metrics. The metrics chosen should best reflect the ambition of the machine learning project.

Evaluation metrics for classification tasks include accuracy, precision, recall, F-measure, gini coefficient and lift. Interpreting the explanations below requires and understanding of confusion matrices. Table 2.1 below gives a confusion matrix.

Table 2.2: Confusion matrix

		Predicted class	
		Negative	Positive
Actual class	Negative	True negative (TN)	False positive (FP)
	Positive	False negative (FN)	True positive (TP)

Accuracy is a measure of the total correct predictions over all predicted outcomes. Accuracy is sensitive to the cut-off value for classification and the underlying distribution of the label variable. Accuracy is calculated as the following;

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

Precision is the measure of accuracy in predicting the positive class. It is sensitive to class imbalance and the cut-off value for the classes. It is useful to maximise precision when the penalty for incorrectly predicting the positive class is high. Precision is calculated as follows;

$$precision = \frac{TP}{TP + FP}$$

Recall measures the proportion of the positive class that is correctly predicted. As above, recall is sensitive to the cut-off for the class and to class imbalance. Recall is useful when there is a high cost associated with false negative predictions. Recall is calculated as follows;

$$recall = \frac{TP}{TP + FN}$$

F-measure, also known as F1 score, combines the results of recall and accuracy and is therefore useful when there is an equal cost associated with false positives and false negatives. F-measures are less sensitive to class imbalance and cut-off values. The calculation of F-measure is given below;

$$F = 2 \cdot \left(\frac{precision \cdot recall}{precision + recall}\right)$$

AUC (Area Under Curve) is a measure of the model performance and is independent of cut-off values and class imbalance. AUC measures the area under a receiver operating curve over the random guess curve. The receiver operating curve plots the true positive ratio (TPR) and false positive ratio (FPR) against all possible classification cut-off values in order. The result is a concave curve sitting above the random guess curve. AUC is useful as an overall measure of the performance of a classification performance of a model independent of the chosen cut-off value. The gini coefficient is often also quoted alongside AUC, however since the two measures are positively linearly related, the gini coefficient provides no additional value. AUC is given by the below expression;

$$AUC = \frac{1}{mn} \sum_{i=1}^{m} \sum_{j=1}^{n} 1 p_i > p_j$$

Prediction tasks involving a continuous dependent variable cannot be evaluated in the same way as a classification problem. Where the previous evaluation metrics assessed the allocative efficiency of models for class attribution, regression problems are typically assessed by the distance of predictions from the true value. Mean square error, coefficient of determination and AIC are common evaluation metrics for regression problems which an assessment of the residuals of a regression model.

Mean square error is the standard deviation of residuals in a regression. It represents the average distance between a predicted record and its corresponding true value. MSE is given by the below;

$$MSE = \frac{1}{n}\sum_{i-1}^{n}(Y_i - \widehat{Y}_i)^2$$

R-squared (coefficient of determination) measures the dispersion of observations about a fitted line. The R square takes on values between 0 and 1 and is said to express the proportion of the dependent variable that is explained by the model. It is calculated as 1 minus the residual sum of squares (SSR) divided by the total sum of squares. Inputs for the coefficient of determination are given as;

$$SSR = \sum(y_i - x_i)^2, \quad SST = \sum(y_i - \bar{y})^2$$

where y_i are recorded observations, x_i are predictions, and $\bar{y}$ is the mean value of the recorded observations.

AIC (Akaike Information Criterion) estimates the probability of minimising information loss through a model and is described as an estimator of out of sample prediction error. Much like other evaluation metrics for regression, the absolute value of AIC is meaningful only in comparison to that of other models. Generally, the model which minimises AIC is has the lowest prediction error and indicates a more parsimonious fit. AIC is especially useful in situations involving low sample size, or where it is not practical to hold a validation dataset (such as time series prediction). AIC uses maximum likelihood estimation (L) in its measurement and penalizes for complex models with a high number of features (k), as described below;

$$AIC = -2\ln(L) + 2k$$

2.4. Summary

The study of financial literacy looks to understand how individuals make complex financial decisions with imperfect information. While early attempts to define financial literacy recognise the importance of financial behaviour and attitude, the measurement of financial literacy has not been so progressive. Researchers and government organisations continue to use narrow financial knowledge surveys to infer a relationship between aptitude and decision making.

Through future research an appropriate definition and measurement construct for financial literacy will take into account behaviours and attitudes while moderating results by contextual factors. This idea is brought to light by Lusardi and Mitchell (2014) who acknowledge that optimal decision making is subjective. Where it may be optimal for one person to make additional superannuation contributions, another person may find it optimal to accrue savings. An optimal framework for defining financial literacy will look to model financial knowledge, attitude and behaviour against an outcomes-based dependent variable.

More work is required to model the complex interactions individuals have with financial markets, institutions and instruments; how those interactions are shaped by context; and the outcomes of these interactions. Applying such a construct to the superannuation industry will have its own set of challenges. As a result, conventional econometric modelling will not be sufficient, more advanced analytical techniques will be required to achieve this task.

3. Financial literacy in superannuation: Empirical evidence for positive financial outcomes and decision making

Financial literacy is a measure of the extent to which an individual actor is able to combine skills, knowledge and experience to make sound financial decisions. Financial literacy is therefore a combination of financial knowledge, financial behaviours and financial attitude. Empirical research fails to recognise this multifaceted definition for financial literacy and experiments are therefore designed around a measure of financial knowledge. Furthermore, no study has attempted to capture the context specific attributes required to describe financial literacy in superannuation. To address these challenges I partner with a leading retail superannuation business in Australia to design and deploy an online member survey for financial literacy which captures financial knowledge, financial behaviours and financial attitude. I report the results of this survey and enrich survey responses with administrative data to identify positive financial behaviours and correlate survey responses to positive financial outcomes. The findings of this work conclude that the proposed construct for financial literacy in superannuation are far more closely correlated to positive financial outcomes.

3.1. Introduction

Financial literacy represents the ability of individuals to make sound financial decisions which enhance their financial wealth and well-being. Given the complex nature of decision making, financial literacy is a construct of numerous elements supporting decision making. The OECD (2014) propose that this construct is comprised of three key elements; financial knowledge, financial behaviour and financial attitude.

Over 90% of all working Australians accumulate retirement savings through compulsory super guarantee (APRA, 2016). Due to a combination of policy reform and product innovation superannuation in Australia has become increasingly complex. In part this has been driven by the move away from defined benefit schemes, towards accumulation funds. Under a defined benefit scheme employers would assume the investment and longevity risk associated with living in retirement.

Through accumulation funds, these risks are shifted to the individual. As a result, the majority of Australians are increasingly confronted by complex financial decisions while managing their retirement savings.

Financial literacy is not only shown to be associated with better investment performance but also better planning and management of finances in retirement (Lusardi & Mitchell 2011b). Highly literate individuals are also more likely to seek help from qualified sources (Chu et al. 2017).

Previous studies confirm that Australians generally have low financial literacy and that low financial literacy is prevalent among the most at-risk groups in society. Low income and poorly educated groups are at the greatest risk of mismanaging their retirement savings (Agnew, Bateman & Thorp 2013). As a result, there is a retirement savings shortfall in Australia. This shortfall is estimated to be A$768bn, or A$70,100 per person including aged pension benefits and it is acknowledged that the current 9.5% super guarantee is not sufficient to address that shortfall in the future (Rice Warner, 2014). With an estimated 5.5 million Australians retiring between 2011 and 2030, a diminishing government safety net and increasingly complex financial decisions, more Australians will be living in poverty during retirement (Hugo & SA 2014).

Past studies have taken a broad view of financial literacy measurement, with financial knowledge commonly used as a proxy for financial literacy. Further, there is a limited understanding of what constitutes financial literacy for superannuation. Due an inability to access administrative data on superannuation members past studies have also been challenged to demonstrate how financial literacy correlates to superior decision making.

To address these challenges have partnered with a leading Australian retail superannuation fund to design, administer and analyse the results of a financial literacy survey. I enrich the results of the survey with behavioural and demographic data and provide an analysis of the results.

The remainder of this chapter is organised into five sections: Section 2 provides an overview and discussion of related work, Section 3 discusses the methodology used in administering the survey, Section 4 provides an analysis of the results of the survey, Section 5 analyses positive decision making in superannuation and Section 6 concludes.

3.2. Related work

3.2.1. Measurement of financial literacy

Financial literacy describes the ability of individuals to make sound financial decisions for lifetime financial security. Definitions for financial literacy often emphasise the interaction between skills and knowledge in order to make effective financial decisions. The OECD (2014) stipulate that the financial knowledge, financial attitude and financial behaviour all contribute to sound financial decision making. Several prominent papers on financial literacy note that there is no single accepted definition for financial literacy (Hung, Parker & Yoong 2009; Huston 2010) and that the body of research on this topic are often divided on the importance of its various dimensions. Furthermore, a review of research papers conducted by Huston (2010) finds that only 13% of papers propose any definition at all.

Despite ongoing disagreement on the definition of financial literacy many studies use financial literacy and financial knowledge interchangeably. Huston (2010) has found that of a review of 71 studies this occurs in 47% of those studies. This is an expected outcome of the limitations associated with measuring financial literacy.

Describing and measuring all of the contributing factors which determine an individual's ability to make financial decisions is a challenging task. The majority of studies base their findings solely on data collected through survey and are subject to low participation rates, with the majority of surveys administered by phone, internet or mail (Huston 2010). As a result, the measurement of financial literacy is often at odds with the proposed definition for financial literacy. This has given rise to a situation whereby financial knowledge is commonly taken as an acceptable proxy for financial literacy. However, test-based measurement of financial literacy has been criticized for failing to demonstrate the suitability of the approach to measuring financial ability. Stolper and Walter (2017) suggest that there is limited evidence to support the stipulation that the commonplace test-based questions for financial literacy are suitable for measuring financial ability.

Test based measures of financial literacy are commonplace, with the Big Three questions first proposed by Lusardi and Mitchell in 2008 becoming an international standard for measuring financial literacy. Numerous studies have extended upon basic knowledge assessments, and introduced questions intended to assess a wider range of knowledge and abilities. The OECD (2014) propose 40 test based questions relating personal finances to establish a greater level of differentiation in the responses. Van Rooij et al. (2011) introduce the concept of advanced literacy covering investment concepts involving stock market participation, bond pricing, diversification and mutual funds.

Noting the numerous drawbacks of test-based measures it has been suggested that an examination of financial behaviours and the resulting quality of decisions would be a more appropriate measure for financial literacy. Stolper and Walter (2017) propose a number of measures such as portfolio diversification, investment experience and propensity to enter complex financial markets. Calvet et al. (2009) study financial decision making using transactional data for equities and propose an index based on mistakes. It is noted by Stolper and Walter (2017) that while this approach is more desirable than a test based measure of knowledge, a large volume of administrative data is required to perform this measurement.

3.2.2. Outcomes of financial literacy

Numerous studies for financial literacy point to a correlation between high financial literacy and positive outcomes. In particular, research points to a higher incidence of retirement planning activities, stock market participation, improved decision making and superior investment performance correlated to high financial literacy.

Performance against test-based measures for financial literacy highlight a strong positive correlation between test-based performance and retirement planning

(Stolper and Walter, 2017). In the United States, Clarke et al. (2017) establish a positive correlation between financial literacy, retirement planning and the investment performance. Lusardi and Mitchell (2007) find that individuals who perform strongly in a test-based knowledge assessment are much more likely to have thought about retirement and understand the concept of compounding interest. Further, they demonstrate in a later study that financial knowledge and retirement planning are positively related while controlling for exogenous factors (Lusardi & Mitchell 2017). In this study they find that the most important factor for retirement planning is performance against a set of sophisticated financial knowledge questions, rather than the common 'Big 3'.

Literature on financial literacy is supportive of the positive correlation between test-based scores and stock market participation. Stolper and Walter (2017) suggest that highly literate investors are more likely to hold stocks and mutual funds, and that the total level of investment in the stock market for individuals is correlated to financial literacy.

Sophisticated investors are less likely to make mistakes, realise losses and are savvier in selecting financial products. As a result, numerous studies demonstrate that individuals with low financial literacy are more likely to pay higher costs of borrowing, select costly credit cards and use them sub-optimally.

There is evidence to suggest that financial literacy and investment performance are also correlated. Stolper and Walter (2017) propose that financially savvy investors invest more efficiently, expect a greater rate of return on stock portfolios and hold more diversified portfolios. Lusardi and Mitchell (2017) find that high financial literacy is correlated to greater planning and in turn, higher wealth accumulation. In another study, Lusardi and Mitchell (2011a) find that those individuals who plan for retirement accumulate three times greater wealth than non-planners, and that the extent and discipline towards planning also impacts wealth accumulation.

3.3. Methodology

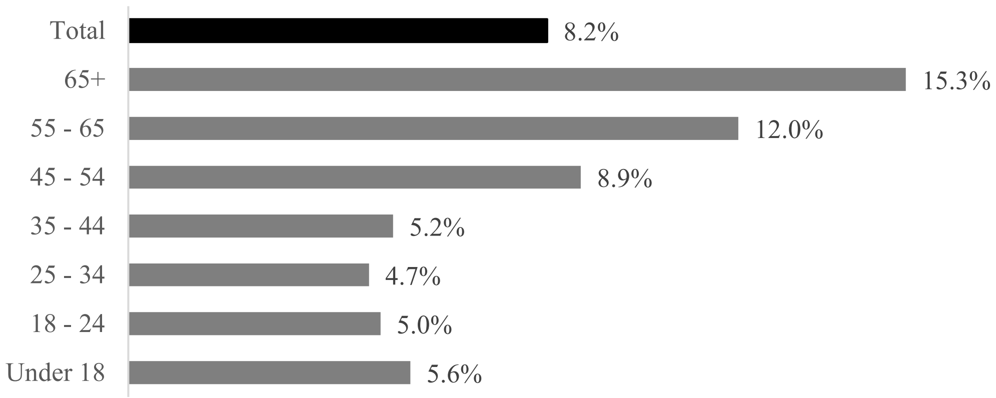
In December 2017 a financial literacy survey was sent to members of a leading Australian retail superannuation fund. An online survey was chosen among the various options (telephone, face to face, mail) in order to maximise the number of respondents while minimising the expense associated with issuing the survey. The industry partner utilised internal systems to issue the survey, eliminating any privacy considerations relevant to the handling of personally identifiable information. A total of 12,463 members received the survey via electronic direct mail and 1,091 members responded.

The survey consists of twenty-four questions including one instructional manipulation check and one financial literacy self-assessment. The questions are broken into 5 categories; basic financial knowledge (4), advanced superannuation knowledge (4), financial attitude (4), financial behaviour (4) and demographics (6). Sixty-three members failed the instructional manipulation check, leaving the remaining 1,028 responses as valid. A number of inferential statistical tests are employed to interpret the results and identify dependencies between variables.

3.4. Survey results

The total response rate to the financial literacy survey was 8.2%. Respondents in the 65 years and over age group responded most positively, with a response rate of 15.3%. Young survey recipients were the least responsive, with only 4.8% of survey recipients under 35 years responding to the survey. The average age of respondents was 54 years, and the average super account balance \$207,445. This is compared to an overall average age of 49 years and account balance \$125,000 for the entire population of survey recipients.

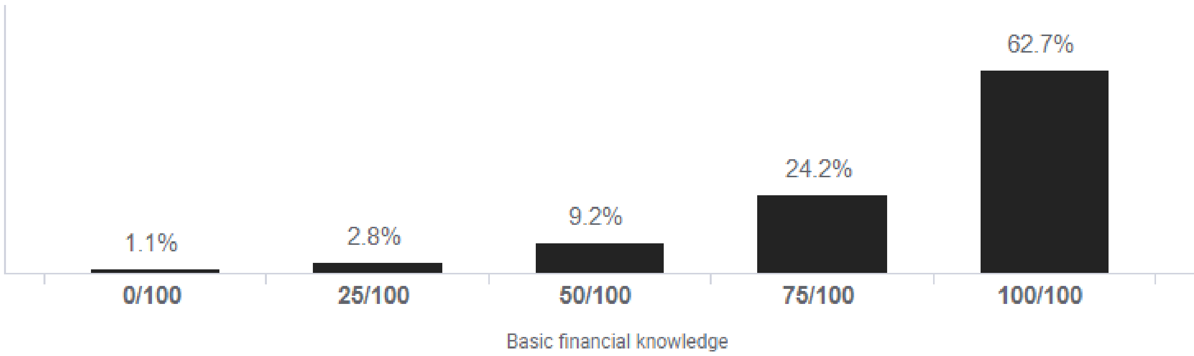
Figure 3.1: Survey response rates



3.4.1. Basic financial knowledge

Basic financial knowledge questions were based on Lusardi and Mitchell (2011b). Overall, 62.7% of survey respondents were able to answer them all correctly and only 13.1% of respondents were unable to answer more than two of the questions correctly. The mean score across all members who responded to the survey was 86.9%.

Figure 3.2: Basic financial knowledge assessment results



Respondents answered all questions with a high level of success. Questions 1 to 3 which deal with the concepts of compound interest, inflation and diversification respectively were on average answered correctly 93.4% of the time. Question 4, which covers the concept of time value of money, was answered correctly by 79.3% of respondents.

These results are not dissimilar to past studies of the Australian population. Bateman, Eckert and Satchell (2012) studied Australian retirement savers and assessment their financial knowledge against a similar question set (questions 1, 2 and 4 are identical between the two studies). While the 2012 study produced lower rates of success against like questions (88.4%, 78.4%, 55.2% respectively), the results of both studies conclude that a greater proportion of respondents struggle to correctly answer questions relating to the time value of money.

Table 3.1: Basic financial knowledge questionnaire

Question	Answered correctly
Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years how much do you think you would have in the account if you left the money to grow…?	93.3% (959)
Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account…?	89.3% (918)
Buying a single company's shares usually provides a safer return than a managed fund…?	97.6% (1,003)
Assume a friend inherits $10,000 today and their sibling inherits $10,000 three years from now. Who is richer because of the inheritance…?	79.3% (815)

The lack of contrast in the performance of survey respondents is problematic. 87% of all respondents are represented by the top two performance bands; 75% and 100%. This presents a challenge in two ways; first, there is very little contrast in order to discern the unique decision making capabilities of members of the fund, and second, statistical analysis and regression modelling typically assume a normally distributed dataset. The absence of normal distribution in the response data violates the assumptions of many statistical and inferential tests and OLS regression. Non-parametric tests ought to be used under these circumstances.

To understand the relationship between these results and key demographics I plot the data, and conduct Fisher's Exact Test for independence. Fisher's is appropriate where the expected frequencies are less than 5.

Visual inspection of the results against Age shows a linear trend in the success rate of the various age groups. On average, older age groups appear to answer the basic financial knowledge questions correctly at a greater frequency. Fisher's Exact Test for independence indicates that I are unable to reject the null hypothesis at 95% confidence. At 90% confidence I reject the null and conclude that Age and Basic financial knowledge are dependent.

```
Fisher's Exact Test for Count Data with simulated p-value (based on 2000
replicates)

data:  Basic_knowledge, Age
p-value = 0.05547
alternative hypothesis: two.sided
```

Visual inspection of Highest level of Education shows a strong positive relationship when education is ordered by level of qualification. Statistical testing supports this conclusion, where Fisher's Exact Test for independence rejects the null at 99% confidence.

```
Fisher's Exact Test for Count Data with simulated p-value (based on 2
000 replicates)

data:  Basic_knowledge, Education
p-value = 0.0004998
alternative hypothesis: two.sided
```

The weekly income variable also appears to show dependence between itself and basic financial knowledge. Statistical testing supports this conclusion at 99% confidence.

```
Fisher's Exact Test for Count Data with simulated p-value (based on 2000
replicates)

data:  Basic_knowledge, Weekly_income
p-value = 0.0004998
alternative hypothesis: two.sided
```

Variation in performance of men and women in financial literacy tests (basic financial knowledge) is well documented in research (Van Rooij, Lusardi & Alessie 2011). As a result, there is a strong expectation of dependence between Gender and Basic financial knowledge. Plotting of the average result by gender shows a sizeable discrepancy in performance. Fisher's Exact Test for independence confirms this expectation at 99% confidence. I therefore reject the null hypothesis and conclude that performance in the basic financial knowledge questionnaire is dependent on gender.

```
Fisher's Exact Test for Count Data with simulated p-value (based on 2000
replicates)

data:  Basic_knowledge, Gender
p-value = 0.0004998
alternative hypothesis: two.sided
```

Figure 3.3: Basic knowledge by demographic group

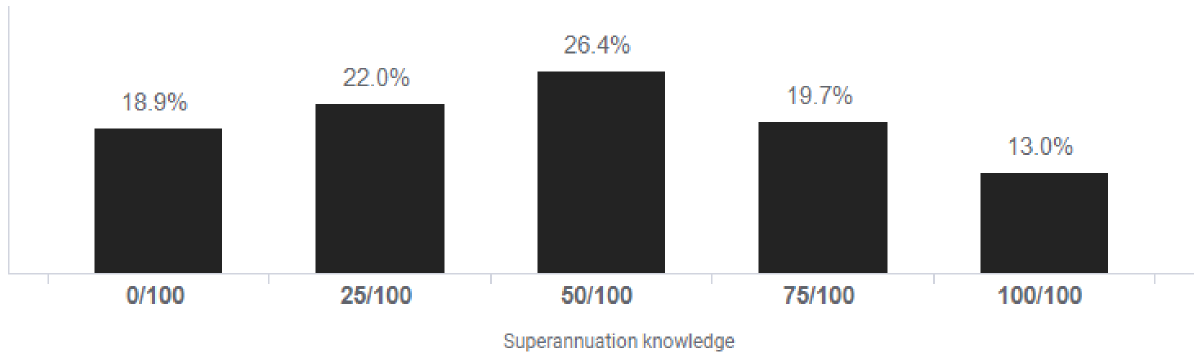
Demographic group	Basic financial knowledge
Age	
18 - 24	84.6%
25 - 34	84.4%
35 - 44	84.4%
45 - 54	87.2%
55 - 65	86.1%
65+	90.5%
Education	
Less than year 12 or equivalent	79.1%
Year 12 or equivalent	81.7%
Vocational qualification	84.2%
Associate diploma	85.1%
Undergraduate diploma	87.2%
Bachelors degree	90.7%
Bachelors degree with honours	88.3%
Postgraduate diploma	92.1%
Masters degree	94.6%
Doctorate	94.8%
Weekly income	
$0	81.3%
$1-199	89.8%
$200-299	75.0%
$300-399	81.8%
$400-499	82.0%
$500-599	89.5%
$600-799	84.3%
$800-999	87.5%
$1,000-1,249	87.5%
$1,250-1,499	84.6%
$1,500-1,999	88.2%
$2,000 or more	92.9%
Gender	
F	82.6%
M	90.3%

3.4.2. Superannuation knowledge

Questions for advanced knowledge pertaining specifically to superannuation form a core component of the financial knowledge assessment. It is my understanding that this is the first time a financial literacy survey has issued questions relating to the Australian superannuation system. As a result, the four questions have been formed for this survey by industry domain experts in a leading retail superannuation business. The four questions relate to taxation of contributions (Q1), contribution caps (Q2, Q3) and the current super guarantee rate (Q4).

The results of this component of the knowledge assessment are more evenly distributed across all performance bands as compared to the basic financial knowledge assessment. Only 13% of respondents answered all questions correctly and 18.9% of respondents were unable to answer any question correctly.

Figure 3.4: Superannuation knowledge histogram



Respondents performed poorly against questions covering contribution caps, with an average result of 36.7% and 20% for questions 2 and 3 respectively.

Table 3.2: Superannuation knowledge questionnaire

Before tax (concessional) payments that you or your employer might make into your superannuation fund are taxed at…?	61.9% (636)
The annual limit for concessionally taxed payments into your superannuation fund is…?	36.7% (377)
The three-year limit for after-tax (non-concessional) payments into your superannuation fund is…?	20% (206)
The current Superannuation Guarantee rate (that is, the rate of contribution your employer is legislated to pay) is…?	70.7% (727)

Average results by age group indicate that younger respondents performed best, though there is low confidence in this result due to the small number of respondents aged 18 – 24 years of age. Financial knowledge deteriorates quickly and then lifts as respondents approach retirement. Retirees (over 65 years of age) answered the lowest number of questions correctly on average. A study carried out by van Rooij et al. (2011) found that financial knowledge is low among the young, peaks at middle-aged and then steadily deteriorates.

Due to the low number of respondents in the 18 to 25 age range, the 95% confidence interval is $36.43 < x < 75.11$, indicating that estimates of the performance of this age group may be inaccurate.

Tests for independence indicate that superannuation knowledge is weakly dependent on age.

```
Fisher's Exact Test for Count Data with simulated p-value (based on 2000
replicates)

data:  Super_knowledge, Age
p-value = 0.05397
alternative hypothesis: two.sided
```

Charting of the education variable against superannuation knowledge indicates a positive correlation between the two variables. Members with a Master's degree performed best, closely followed by those with a Doctorate. The lowest average performance is held by those with year 12 or equivalent and vocational qualifications. I use Fishers Exact test for independence. The results show that superannuation knowledge is strongly dependent on highest level of education.

```
Fisher's Exact Test for Count Data with simulated p-value (based on 2000
replicates)

data:  Super_knowledge, Education
p-value = 0.0009995
alternative hypothesis: two.sided
```

On average the highest performing segments by weekly income are high income earners. Those respondents who earn $2,000 or more per week successfully answered the greatest number of questions on average. Results from the analysis indicate that weekly income and superannuation knowledge are highly dependent at 99% confidence. Interruption to the positive linear trend in Figure 3.5 is explained by high standard deviation in the results of lower income bands. As a result, estimation of the true rate of success is unreliable for these segments.

```
Fisher's Exact Test for Count Data with simulated p-value (based on 2000
replicates)

data:  Super_knowledge, Weekly_income
p-value = 0.0004998
alternative hypothesis: two.sided
```

Performance against the question set by gender again favours males, outperforming female respondents by 4.6%. When outperformance of the male segment is represented as a ratio, it becomes clear that the more challenging superannuation knowledge questions create a greater divide in the gap between men and women. In the basic financial knowledge questionnaire, men outperformed women by 9.04%. In the superannuation knowledge questionnaire that ratio increased to 10.5%. Testing for independence indicates that age and superannuation knowledge are highly dependent at 99% confidence.

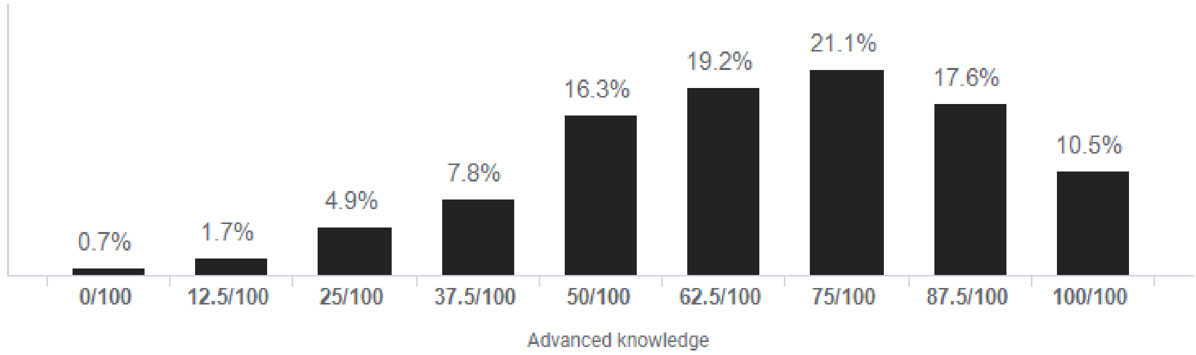
```
Fisher's Exact Test for Count Data with simulated p-value (based on 2000
replicates)

data:  Super_knowledge, Gender
p-value = 0.0004998
alternative hypothesis: two.sided
```

Figure 3.5: Superannuation knowledge by demographic group

Demographic group	Superannuation knowledge
Age	
18 - 24	55.8%
25 - 34	42.7%
35 - 44	50.0%
45 - 54	49.3%
55 - 65	48.5%
65+	42.0%
Education	
Less than year 12 or equivalent	42.2%
Year 12 or equivalent	40.5%
Vocational qualification	40.4%
Associate diploma	52.0%
Undergraduate diploma	43.6%
Bachelors degree	52.6%
Bachelors degree with honours	47.3%
Postgraduate diploma	49.4%
Masters degree	56.7%
Doctorate	55.2%
Weekly income	
$0	34.7%
$1-199	35.2%
$200-299	40.2%
$300-399	32.4%
$400-499	28.1%
$500-599	46.8%
$600-799	34.9%
$800-999	41.0%
$1,000-1,249	45.3%
$1,250-1,499	48.2%
$1,500-1,999	53.5%
$2,000 or more	58.6%
Gender	
F	45.0%
M	49.2%

The composite score composed of basic financial and superannuation knowledge provides a range of outcomes across the nine performance bands. The aggregation of these two knowledge assessments provides a greater level of nuance between the survey respondents.

Figure 3.6: Composite financial knowledge assessment results



3.4.3. Financial attitude

Financial attitude describes the complex processes which influence decision making in individuals. Financial attitude describes an individual's beliefs towards financial management, risk taking and decision making. It also includes an individual's subjective assessment of their ability to understand, interpret and execute financial decisions that are put in front of them.

Four financial attitude questions were issued, targeted at understanding survey respondents' attitudes towards superannuation and their level of confidence in their own understanding of financial matters.

Questions 1 and 2 are represented to survey recipients as statements. Respondents are then asked to indicate their level of agreement with the statement against a seven point qualitative scale provided.

On average 55% of respondents agree that they have a greater level of interest in superannuation than their friends. Only 16% of respondents disagree to some extent with the statement. Those who agreed with the statement have an average balance of $248,074 compared to $121,900 for those who disagreed. Those in agreement the statement on average scored 19.5 more points in the composite advanced financial knowledge questionnaire with an average result of 73.8. Both groups have an average age of 53.8 years.

Question 2 looks to understand the perceived importance of superannuation as a component of retirement income. The question states the following; 'I believe superannuation doesn't matter as the government will cover any gap in my retirement income'. The overwhelming majority of respondents (90.7%) disagree with this statement to some extent and thus recognise the role of superannuation savings in retirement. A small number of respondents (4.6%) agree with the statement, indicating an expectation that the government will provide for their needs during retirement through the aged pension. There is no statistically significant difference in the account balance or age of those who agreed with the statement compared to those who disagreed. Respondents who disagreed with the statement scored 11.5% higher on the advanced knowledge questionnaire. A two sample T test validates this result at 99% confidence.

Table 3.3: Financial attitude

	Entirely disagree	**2**	**3**	**4**	**5**	**6**	**Entirely agree**
Compared to my friends I have a greater level of interest in superannuation	3.8% (39)	4.9% (50)	7.3% (75)	28.9% (297)	17.4% (179)	20.2% (208)	17.5% (180)
I believe superannuation doesn't matter as the government will cover any gap in my retirement income	55.5% (571)	25.8% (265)	9.4% (97)	4.7% (48)	2.8% (29)	0.8% (8)	1% (10)
	Daily	**Weekly**	**Monthly**	**Quarterly**	**6 monthly**	**Annually**	**Never**
I think about my superannuation	9.5% (98)	18.9% (194)	27.1% (279)	18.9% (194)	13.1% (135)	9.2% (95)	3.2% (33)

Question 3, 'I think about my superannuation…' shows that the most common frequency is monthly, followed by weekly and quarterly equally. Respondents who state that they think about their super quarterly or more frequently have an average balance of $231,070, compared to $138,726 for those who think about their super less frequently than quarterly. Those who think about their super frequently score

10.5% higher in the financial knowledge questionnaire. There is no statistical significant difference in the average age of the two groups. Lusardi and Mitchell (2010) use a similar question to represent retirement planning and through their analysis conclude that older, better educated, male respondents are more likely to plan for their retirement.

3.4.4. Financial behaviour

Financial behaviour is an important component of financial literacy. It describes the habits that individuals adopt in managing their finances. Financial behaviours are guided by the financial knowledge and attitudes. The questionnaire on financial behaviours seeks to understand the habits of superannuation members in managing their retirement savings. This includes reading their account statements, taking the time to understand the periodic performance of their accounts, and knowledge of the investments which drive that performance. The questionnaire also looks to understand the extent to which members engage in conversation about their retirement savings.

Table 3.4: Financial behaviour

	Entirely disagree	**2**	**3**	**4**	**5**	**6**	**Entirely agree**
I know which investment options my super is invested in	4.8% (49)	6% (62)	4.4% (45)	13.9% (143)	5.4% (55)	25.5% (262)	40.1% (412)
I know how my superannuation performed in the last 12 months	4% (41)	4.8% (49)	5.3% (54)	18.5% (190)	6% (62)	27.2% (280)	34.2% (352)
I know how much money I have in my superannuation	2% (21)	1.8% (18)	2.3% (24)	1.4% (14)	9.1% (94)	22.2% (228)	61.2% (629)
	Daily	**Weekly**	**Monthly**	**Quarterly**	**6 monthly**	**Annually**	**Never**
I talk to friends and family about superannuation	1% (10)	4.6% (47)	14.6% (150)	15.2% (156)	16.5% (170)	20.2% (208)	27.9% (287)
	Don't recall receiving a statement			**No**		**Yes**	

Do you read your bi-annual superannuation statement?	7.7% (79)	14.7% (151)	77.6% (798)

Question 1, 'I know which investment options my super is invested in', highlights the overall positive engagement the survey sample have with their superannuation. Over 70% of all respondents know how their retirement savings are invested. Super members who do know how their savings are invested perform better in the financial knowledge questionnaire (70.9% compared to 51.7% for those who disagree), and hold substantially higher account balances ($227,146, compared to $141,951). The average age of respondents in agreement with the statement is 54.5 years, compared to 52.6 years for those in disagreement with the statement. There is no statistically significant difference in age between the two groups.

Question 2 looks to understand whether super members understand and actively track the performance of their investments. Over 67% of survey respondents agree with the statement, indicating that they do know how their fund has performed. Members who responded in agreement with question 2 are marginally older than the alternative cohort of members with an average age of 55 years, compared to 51 years for those in disagreement with the statement. Members in agreement have account balances which are on average $83,638 higher, and they perform 15 points better in the financial knowledge assessment.

Question 3 establishes whether superannuation members are actively monitoring their account balance. Agreement with the statement requires ongoing engagement with superannuation. High level results show that 92.5% of survey respondents know how much money they have in superannuation savings. Members who responded in agreement with the statement are on average 6 years older, with an average age of 54.6 years. They hold an average account balance of $213,428 and score 15.5% higher on the financial knowledge assessment than those in disagreement with the statement.

Regularly engaging in conversation about superannuation is hypothesised to indicate a high level of engagement and is positive financial behaviour. Few members speak about their super monthly or more regularly. The most common response to question 4 is Never, followed by *Annually*. Survey respondents who discuss their super with friends or family regularly (defined as quarterly or more frequently) do on average perform better in the financial knowledge assessment by 10%. There is no statistically significant difference in age or account balance between the two groups.

3.4.5. Self-assessed financial literacy

In financial literacy research, confidence is defined as the subjective measurement of financial literacy offered by individuals. In the survey, I used a Likert scale ranging from poor to excellent and ask survey recipients to rate their financial knowledge. Survey respondents who indicated that they had a good to excellent understanding of financial matters have higher account balances and score well in the advanced financial knowledge questionnaire compared to their peers who self-assessed their financial knowledge at fair or worse. Respondents who self-assess as having good knowledge have an average balance of $233,790, compared to $150,969; and score 73.4% in the knowledge questionnaire, compared to 53.7%. Both groups have an average age of 54 years. All comparisons have been validated using two-sample T tests.

Overconfidence and under-confidence are represented by the variation between the subjective and objective measures of financial knowledge. Confidence has a role to play in financial decision making, a key component of financial literacy. Research suggests that the interaction between subjective and objective financial literacy plays an important role in the ability of individuals to take action to enhance their financial well-being. Stolper and Walter (2017) report that both objective and subjective measures of financial knowledge are predictive of retirement planning and stock market participation. Further, Hadar, Sood and Fox (2013) find that the interaction between subjective and objective knowledge may support or deteriorate the ability of individuals to act. Those who have high subjective knowledge relative to objective knowledge, are more likely to make risky investments.

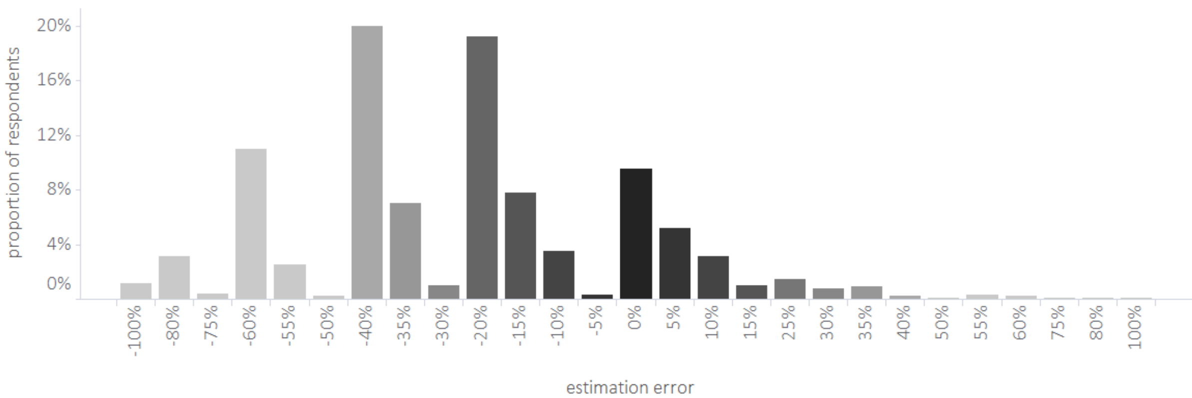
On average, respondents in the survey underestimate their financial abilities by 26% as described by the basic financial knowledge. Survey respondents overestimate their abilities on average by 13% with respect to the superannuation knowledge assessment. Using the composite advanced knowledge score, respondents underestimate their level of financial knowledge by 6.25%. This effect is in opposition with other research which has found that individuals tend to exhibit overconfidence, rating themselves more highly than their objective financial knowledge score (Stolper & Walter 2017).

Stolper and Walter (2017) find that women typically demonstrate lower confidence in their financial abilities. The findings support this hypothesis with women on average underestimating their financial abilities by 7.6%, compared to men who underestimate their abilities by 5.2% when assessed against the advanced financial knowledge objective measure.

Table 3.5: Self-assessment performance

	Poor	**Not very good**	**Fair**	**Good**	**Very good**	**Excellent**
How would you assess your understanding of financial matters	2% (112)	7.1% (233)	22.7% (328)	31.9% (73)	25.4% (21)	10.9% (261)

Figure 3.7: Self-assessment error – Basic financial knowledge



Analysis of correlation coefficients highlight a weak to moderate positive correlation between the subjective and objective measurements of financial knowledge. The results show that survey respondents are less accurate in assessing their basic financial knowledge, often underestimating their abilities, while they are more accurate in assessing their superannuation knowledge.

Figure 3.8: Self-assessment error – Superannuation knowledge

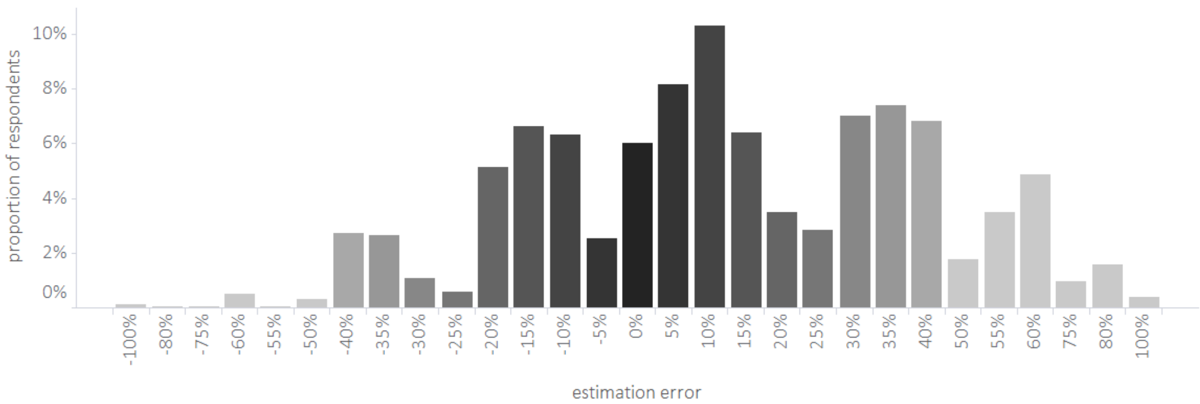


Table 3.6: Correlation coefficients for subjective and objective knowledge

Correlation coefficient	**Basic knowledge**	**Superannuation knowledge**	**Composite knowledge**
Self-assessed knowledge	0.278932	0.509425	0.511327

3.5. Association to positive outcomes

3.5.1. Risk, return and account balance

To assess positive outcomes against the comprehensive financial literacy measure I utilise several metrics; account balance, investment return, and portfolio risk. I use multivariate regression analysis to provide insight into the direction and magnitude of effect of the independent variables and I control for age to eliminate bias associated with this variable. Furthermore, I determine the level of predictive power of the proposed construct for financial literacy and compare to the common 'Big 3' test-based measure to assess the overall efficacy of the model. In this regression, financial outcomes are treated as dependent variables and the components of the financial literacy measure are independent variables where V is account balance, μ is portfolio return and σ is portfolio volatility, as below:

$$V = \beta_0 + \beta_1 Attitude + \beta_2\ Behaviour + \beta_3 Knowledge \quad (1)$$

$$\mu = \beta_0 + \beta_1 Attitude + \beta_2\ Behaviour + \beta_3 Knowledge \quad (2)$$

$$\sigma = \beta_0 + \beta_1 Attitude + \beta_2\ Behaviour + \beta_3 Knowledge \quad (3)$$

Where V is account balance, μ is portfolio return and σ is portfolio volatility.

Regression results from Table 3.7 indicate that age is a strong predictor for all three outcomes. As expected the coefficients for risk and return are negative, indicating a gradual de-risking of portfolios as members approach retirement. The coefficient for account balance is positive and in line with expectations.

Table 3.7: Regression results – Risk, return and account balance

	Risk			**Return**			**Account balance**		
Variable	**Coefficient**	**P**	**Sig**	**Coefficient**	**P**	**Sig**	**Coefficient**	**P**	**Sig**
(Intercept)	4.20E-03	0.0000	***	6.31E-04	<2e-16	***	-218981	0.0478	*
B1	8.43E-06	0.9791		-1.18E-05	0.6867		764	0.9858	
B2	5.44E-04	0.0463	*	4.54E-05	0.0662	.	59242	0.1023	
B3	2.61E-04	0.2775		2.65E-05	0.2229		493	0.9877	
B4	4.43E-05	0.8250		9.60E-06	0.5969		40950	0.1242	
S1	1.42E-04	0.4729		1.99E-05	0.2677		-15651	0.5525	
S2	1.75E-04	0.3729		1.13E-05	0.5263		23260	0.3716	
S3	5.30E-04	0.0227	*	3.82E-05	0.0702	.	-4486	0.8846	
S4	-2.73E-05	0.8884		-3.99E-06	0.8212		-4928	0.8490	
interest	1.78E-04	0.0070	**	1.03E-05	0.0846	.	19956	0.0230	*
believe	-5.39E-05	0.4351		-6.80E-06	0.2774		-14430	0.1163	
think_about	-1.35E-04	0.0388	*	-1.40E-05	0.0180	*	-17574	0.0432	*
self_assess	1.68E-04	0.0583	.	1.57E-05	0.0520	.	20788	0.0787	.
know_balance	-1.09E-05	0.8955		2.71E-06	0.7200		-11264	0.3091	
know_options	1.14E-04	0.0756	.	9.03E-06	0.1208		5142	0.5468	
know_return	-1.08E-04	0.1350		-6.06E-06	0.3546		-985	0.9183	
talk_to	-1.70E-06	0.9770		-5.01E-06	0.3478		6374	0.4153	
statement	4.13E-05	0.7182		-4.21E-06	0.6851		5657	0.7103	
age	-5.07E-05	0.0000	***	-5.80E-06	<2e-16	***	4773	0.0000	***

Statistically significant predictors of portfolio risk with positive coefficients are; Basic knowledge question 2 (inflation), Super knowledge question 3 (non-concessional contribution cap), and stated level of interest in superannuation. This implies that survey respondents who have a high level of interest in their superannuation, and can correctly answer questions relating to inflation and contribution caps are more likely to assume a higher level of portfolio volatility while controlling for age. Members who think about their super more often are also likely to assume greater portfolio volatility (as the value for the highest frequency takes on the lowest numeric value, the coefficient for this variable is negative). To a lesser extent, survey respondents who self-assess their financial knowledge as high, and those who state that they know how their savings are allocated across the investment option menu are also more likely to assume greater portfolio risk.

Survey respondents who state that they think about their superannuation more frequently are more likely to enjoy higher portfolio returns while controlling for age. Basic knowledge question 2, Super knowledge question 3, stated interest, and self-assessed knowledge are also statistically significant predictors at greater than 90% and less than 95% confidence.

Predictors for account balance are; stated interest in superannuation, and members who regularly think about their super. Self-assessed financial knowledge is also a predictor of account balance at 92% confidence. The model for account balance is able to explain the lowest amount of variation in the dependent variable, with a coefficient of variation of 0.1529.

The results in Table 3.8 show that on average the regression models for the comprehensive financial literacy construct explain 17% of the variation in the dependent variables. On average, regression models trained using basic financial literacy survey explain 2% of the variation in the dependent variables. The proposed construct for comprehensive financial literacy outperforms the baseline model substantially, with lift of x7.1, x11.2 and x8.9 for account balance, investment return and portfolio risk respectively.

Table 3.8: Regression results, coefficient of determination

Coefficient of determination	**Account balance**	**Investment return**	**Portfolio risk**
Basic financial knowledge	0.0215	0.0188	0.0209
Superannuation financial literacy	0.1529	0.2103	0.1852
performance ratio	x7.1	x11.2	x8.9

3.5.2. Saving behaviour and tax effective contributions

I analyse the proportion of contributors over a 12 month period for both pre-tax concessional contributions and after-tax non-concessional contributions. Of the survey respondents, 20.9% make after-tax non-concessional contributions, while 13.2% make pre-tax concessional contributions. I make no assumption about the relationship between financial literacy and the dollar amount or frequency of contributions, rather I hypothesis that fund members who hold a higher level of financial literacy are likely to contribute at a greater rate. As a result, this study provides an analyses based on a binary variable for each contribution type, contributors and non-contributors. I use logistic regression to evaluate the impact of individual variables in the construct for financial literacy on the outcomes variables I select and use an up-sampling algorithm to balance the binary variable. I include an intercept for each of the logistic regressions as the rate is not expected to be zero at the origin, and include age as a controlling variable.

Regression analysis shows that fund members who make additional tax effective contributions (concessional) perform well in the knowledge assessment; they know the annual concessional cap, the current employer contribution rate and the relevant tax rate. In addition, they report that they know which investment options they are invested in and regularly speak to friends and family about superannuation. The largest positive effects on concessional contribution rates are superannuation questions 1 and 2. Survey respondents who correctly answer the question, ‘The annual limit for concessionally taxed payments into your superannuation fund is…?’ have an 82.6% greater probability of having made a concessional contribution. Survey respondents who correctly answer ‘Before tax (concessional) payments that you or your employer might make into your superannuation fund are taxed at…?’

have a 66% greater probability of having made a concessional contribution and survey respondents who strongly agree that they know which investment options they have allocated have a 56.3% greater probability of having made a concessional contribution.

I segment survey respondents by those who have contributed in the 12 month observation period and those who have not and analyse the relative frequencies, as reported in Table 3.9. Based on the results of this segmentation I find that members who have made a concessional contribution during the period score higher across the knowledge and behaviour literacy measures. Members with at least one contribution scored 20% higher in the knowledge assessment and 4.7% higher for financial behaviours. The difference was negligible between the groups for financial attitude. Contributing members scored 3.5% higher in the basic financial knowledge assessment.

Voluntary non-concessional contributions are largely driven by age. Regression analysis shows a strong positive coefficient for member age and total non-concessional contributions. Segmentation of the contributing cohort shows a narrow increase in all literacy measures against non-contributors. Contributors score 2.5% higher in knowledge, 4.3% higher in attitude and 2.3% higher in behaviour. By comparison, contributing members 1.3% performed lower than non-contributors for the basic financial knowledge assessment.

Table 3.9: Avg. literacy scores by contribution status (12 months)

	Knowledge	**Attitude**	**Behaviour**	**Basic knowledge**
No concessional contribution	64.3	44.6	76.9	86.1
Concessional contribution	77.2	44.9	80.5	89.1
No non-concessional contribution	65.9	43.8	77.2	86.7
Non-concessional contribution	67.6	45.7	79.0	85.6

Finally I aggregate and standardise the financial literacy measures and assess their classification performance against the two binary variables (Table 3.10). The results indicate that the superannuation literacy measure outperforms basic financial knowledge for accuracy, precision and F1 for voluntary concessional contributions, and against all measures for non-concessional contributions. The superannuation literacy model underperforms as measured by recall for voluntary contributions.

Table 3.10: Classification performance – voluntary contributions

Concessional contributions

	Superannuation literacy	**Basic financial knowledge**
Accuracy	0.636702	0.517669
Precision	0.59894	0.511173
Recall	0.837037	0.903704
F1	0.349125	0.326494

Non-concessional contributions

	Superannuation literacy	**Basic financial knowledge**
Accuracy	0.501311	0.488204
Precision	0.508653	0.501288
Recall	0.862245	0.744898
F1	0.319924	0.299641

3.5.3. Number of investment options

I analyse the number of investment options held survey respondents and the corresponding responses. As depicted in Table 3.11, 45% of survey respondents hold only one option and 74% hold three options or less. The tendency for Australian savers to allow their funds to go into the default fund, rather than exercising choice has been cited as a source of significant opportunity loss (Bateman et al. 2012) and it is estimated that as many as 85% of all superannuation account holders are invested in the default fund. Multiple regression indicates that there is a positive correlation between the total number of investment options and financial knowledge scores. In particular, questions dealing with asset diversification and the prevailing super guarantee rate were most critical to the model. As shown in Table 3.11, increasing financial knowledge scores are associated with higher average number of options held per portfolio.

Table 3.11: Number of investment options per account

Basic financial knowledge	**0**	**12.5**	**25**	**37.5**	**50**	**62.5**	**75**	**87.5**	**100**
Avg. number of options	2.40	2.43	2.51	3.26	2.90	3.54	3.84	4.11	4.46
Median number of options	1	1	1	2	2	2	2	2	3

Super financial literacy	**10**	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**
Avg. number of options	1.00	2.00	3.00	3.14	3.10	3.52	3.72	4.14	5.50
Median number of options	1	1	1	1	1	2	2	2	5

3.6. Conclusion

Due to the evolving nature of the retirement savings system in Australia there is a growing need for individuals to possess greater levels of financial sophistication. The path to retirement is now fraught with complex decisions involving diversification, tax, investment risk, liquidity and timing risk, and longevity risk. This study explores a construct for financial literacy within the context of superannuation formed through insights from a survey of superannuation members. Analysis of the results indicates that a number of the findings against key demographic variables are consistent with other research involving financial literacy. The findings demonstrate that males, the highly educated and highly paid have the highest levels of financial literacy among superannuation members. The results further indicate that middle-aged members possess the highest levels of financial knowledge. In contrast to other studies, this study concludes that the correlation between age and financial knowledge is low.

Analysis of positive financial outcomes and decisions provides findings which support the proposed construct for financial literacy in superannuation. Insights from this analysis shows that survey respondents who possess higher financial literacy are likely to have higher account balances, higher returns and assume a greater level of risk compared to a similarly aged member. Highly financially literate members are more likely to make voluntary contributions and hold a more diverse portfolio with a greater number of investment options.

This study serves as a foundation to expand the definition for financial literacy in superannuation. Through the inclusion of a superannuation specific knowledge assessment, and behavioural and attitudinal attributes I am able to demonstrate a construct for financial literacy more closely tied to positive decision-making and financial outcomes.

4. Predicting financial literacy in superannuation using debiased multi-output regression

Due to the obligatory nature of the retirement savings system in Australia, the entire Australian workforce participate in a complex financial system without the requisite skills and knowledge to safely navigate the pitfalls of the financial markets, while maximising their retirement savings. As trustees, superannuation funds have a responsibility to their members. A practical solution for the ongoing measurement and monitoring of financial literacy in superannuation is a valuable tool for trustees interested in safeguarding their members' retirement wellbeing. In the past financial literacy research has relied on active participation of individuals to measure financial literacy. Research has so far failed to deliver a context specific measurement construct for financial literacy in superannuation while also demonstrating measureable positive outcomes associated with high financial literacy. In the previous chapter I presented the results of a financial literacy survey and an analysis of its construct. Through this I have demonstrated that the proposed construct for superannuation literacy is superior in predicting positive outcomes. Using this construct and the underlying survey data, this chapter addresses the above challenges and proposes a novel prediction framework trained on passive administrative data from a leading Australian superannuation fund. I use a novel approach to addressing non-response bias and employ advanced machine learning algorithms to maximise predictive performance. The proposed measurement and prediction framework is demonstrated to perform strongly against the test dataset and has substantially higher correlation to positive financial outcomes than the conventional measurement construct for financial literacy.

4.1. Introduction

Since 1991 Australian employers have been required to contribute as a percent of income to the retirement savings of all employees. For this reason, the superannuation industry is very unique; participation is obligatory, short term gains cannot be realised and withdrawals from the system not allowed until retirement. This means that the entire Australian workforce are investors in the often complex assets sold by super funds. In the years to come government funding for retirement will progressively diminish and Australians will increasingly rely on superannuation savings during retirement. The decisions that Australians make with respect to their superannuation and retirement planning will have substantial consequences for their ability to live comfortably during retirement.

Financial literacy is the concept that describes an individual's 'ability to make informed judgements and to take effective decisions regarding the use and management of money (Gerrans, Clark-Murphy & Truscott 2009, p. 420)'. The OECD (2013) propose that financial literacy as a measure for effective financial decision-making is supported by three core competencies; financial knowledge, financial attitude and financial behaviour. While the majority of studies fail to provide a definition for financial literacy (Huston, 2010), or use financial knowledge as a proxy, recent studies generally accept the multifaceted nature of financial literacy. As an extension to the definition described by the OECD (2013), Santini et al. (2019) propose that financial attitude, financial knowledge, and financial behaviour along with individual demographics are antecedents of financial literacy which is further moderated by a number of macroeconomic and political factors.

In the context of superannuation, financial literacy has far-reaching implications for the well-being of the Australian population and their ability to maximise the effectiveness of investment choice and retirement planning. Van Rooij, Lusardi and Alessie (2011b) propose that the failure of individuals to plan for their retirement is predicated upon a lack of financial literacy. Measuring individual financial literacy is a valuable activity for financial institutions interested in safeguarding their customers' financial interests. This is especially true for superannuation funds who offer sophisticated financial products to everyday Australians from all walks of life. Super funds have a responsibility as trustees to enhance member outcomes and as such, must ensure that their members have the appropriate knowledge and skills to manage their retirement savings.

In recent years public policy has recognised the need for a greater prioritisation of financial literacy education. While these programs are shadowed by a cloud of doubt regarding their cost effectiveness and efficacy (Willis, 2011), there remains a strong body of evidence which points to the positive outcomes of financial education. Paraboni and Costa (2021) demonstrate through a study of Brazilian university students that financial literacy measures are comprehensively lifted following the completion of a financial literacy course. Further, a study of financial education in the workplace in the United States has shown that financial education programs are likely to stimulate savings behaviour (Bernheim & Garret, 2003).

Past efforts to measure financial literacy have been constrained by the limitations and biases associated with self-selection surveys. Financial literacy measurement requires active engagement to measure subjects and is therefore subject to non-response bias. Non-response bias refers to the phenomenon in which the respondents possess certain traits (e.g., age and behavioural) that make them non-representative to the whole population, i.e., the conclusions drawn from the respondents may not be applicable to the population. In this study, the financial literacy information is collected via survey, and hence is also subject to non-response bias. In this study, the number of respondents, though sufficient for a typical social science study, is still significantly lower than the size of population, and therefore making the passive measure of financial literacy prone to non-response bias and less reliable. Since the features corresponding to those traits (e.g., age) no longer follow the true underlying distribution in the population, they represent the peculiarities of the data to some extent, and hence introduce the risk of overfitting. Besides, the financial literacy of each customer is represented by several dependent variables, which makes the problem more difficult as multiple output variables need to be modelled simultaneously. To overcome these barriers, in this study, I propose the **Debiased Multi-output Regression (DMR)** framework, which can passively and unbiasedly predict the financial literacy of any customers.

4.2. Related work

4.2.1. Prediction of financial literacy

To date research has consistently failed to match the measurement of financial literacy to an appropriate measurement construct. Hastings, Madrian and Skimmyhorn (2013) suggest that a common challenge researchers face in designing experiments for financial literacy is access to the vast quantities of administrative data required to derive deeper insights and conclusions.

As a result, methodologies applied to research in financial literacy generally lack the sophistication expected for such a complex definition; derived from the beliefs, behaviours, knowledge and financial outcomes of individuals. Review of existing research indicates that the findings for financial literacy are based on descriptive statistics (Gallery, Newton & Palm 2011; Gerrans, Clark-Murphy & Truscott 2009; Hadar, Sood & Fox 2013; Hill & Perdue 2008; Lusardi & Mitchell 2011a, 2011b; Servon & Kaestner 2008), ordinary least squares regression (Agnew, Bateman & Thorp 2013; Chu et al. 2017; Ibrahim & Alqaydi 2013; Lusardi & Mitchell 2007), logistic regression (Potrich, Vieira & Kirch 2015), instrumented variables (Lusardi & Mitchell 2014), and generalized method of moments (Van Rooij, Lusardi & Alessie 2011a; Van Rooij, Lusardi & Alessie 2011b). Li (2020) proposes a using text mining as a novel approach to; directly measure financial literacy scores through text data or, inform the construct of more meaningful survey questions for the measurement of financial literacy. While such a proposal has not yet been put into practice through any known study, there are significant limitations associated with the proposed solution. Text mining for financial literacy measurement in practice would require extensive access to a vast set of text data for individuals. In an industry such as retirement and superannuation, where customers are highly unengaged, availability to such data would be unlikely. While regression is a strong tool for economists it cannot effectively capture the complex patterns and relationships between variables where behavioural features are included.

Given that there is a lack of research supported by large quantities of administrative data there is little evidence to suggest that advanced analytical techniques have ever been applied to financial literacy study.

4.2.2. Multi-output Regression

Multi-output regression, also known as multi-target regression, aims to simultaneously predict multiple real-valued dependent variables. While traditional supervised learning algorithms focus on predicting a single output, multi-output regression arises in many real-world tasks, such as personality traits prediction (Vo et al. 2021), river quality prediction (Džeroski, Demšar & Grbović 2000), and drug efficacy prediction (Li et al. 2017), in which the model must predict multiple outputs for each input.

A straightforward solution is to train multiple traditional models and each corresponds to one output, e.g., five models for predicting the five personality traits. Nevertheless, such as method, known as direct wrapper method, ignores the potential interactions among outputs (e.g., one personality trait may correlate to another), and hence the prediction capability is not maximised. To utilise the interactions among outputs, the chained wrapper method is often used instead, which creates a sequence of models where the output predicted by the first model becomes the additional input to the second, and so on. More recently, some supervised learning algorithms, which were originally designed for single output learning, have been modified to inherently support multi-output learning, such as multi-output k-nearest neighbour (kNN) (Zhang & Zhou 2007), multi-output decision trees (Appice & Džeroski 2007), and multi-output random forests (Kocev et al. 2013). In this study, I will empirically study the performance of these multi-output regression techniques on the prediction task of financial literacy.

4.3. Prediction framework

In this section, I introduce the Debiased Multi-output Regression (DMR) framework, which performs multi-output regression and leverages the unlabelled data to identify features corresponding to the non-response bias.

4.3.1. Problem definition

Formally, let $D_s = \{(\boldsymbol{x}_1, \boldsymbol{y}_1), (\boldsymbol{x}_2, \boldsymbol{y}_2), \dots, (\boldsymbol{x}_n, \boldsymbol{y}_n)\}$ be a set of n training examples corresponding to the n survey respondents, where $\boldsymbol{x}_i = (x_i^1; x_i^2; \dots; x_i^d)$ is the input vector of d independent variables, and $\boldsymbol{y}_i = (y_i^1; y_i^2; \dots; y_i^l)$ is the output vector of l real-valued dependent variables. Let $D_p = \{\boldsymbol{x}_1, \boldsymbol{x}_2, \dots, \boldsymbol{x}_m\}$ be the set of m unsurveyed customers, where $n \ll m$. The task is to learn a model h that can accurately predict the outputs $\boldsymbol{y}_i$, that is, minimising the prediction error $\sum_{i=1}^{n} f_e(h(\boldsymbol{x}_i), \boldsymbol{y}_i)$, where $(\boldsymbol{x}_1, \boldsymbol{y}_1) \in D_s$ and f_e is an error metric function. The data set D_p, though not directly used in the evaluation, can be potentially used to reduce the bias in D_s.

4.3.2. Identifying non-response bias

Since D_s and D_p contain the same set of features, the same feature from either data set should follow the same distribution. However, when non-response bias exists, the feature that cause the bias will have a different distribution, and it should not be used during training. Following this idea, I propose to use the Kolmogorov–Smirnov test, which quantifies the distance between the empirical cumulative distribution functions (CDF) of the same feature in D_s and D_p.

Formally, the CDF is defined as $F(x^d) = \frac{1}{|D|}\sum_{j=1}^{|D|} I_{(-\infty,x^d]}(x_i^d)$, and I compute the CDF for D_s and D_p as $F_s(x^d)$ and $F_p(x^d)$, respectively, for the feature x^d. Then, I compute calculate the maximum absolute difference between $F_s(x^d)$ and $F_p(x^d)$ as $b_d = \sup_{-\infty<x^d<\infty}\left|F_s(x^d) - F_p(x^d)\right|$. When b_d exceeds a user-defined threshold, I say the feature is contributing to the non-response bias and should be excluded from the training.

4.3.3. Chained multi-output regression

For multi-output regression, I permute the target variables into a chain, and the prediction of the first target variable in the chain becomes the input for the prediction of the next target variable. To be specific, let $O = (Y_1, Y_2, \dots, Y_l)$ denote the ordered chain of l target variables, then I predict the first variable Y_1 with the input variables as a standard regression task. After that, the prediction of Y_1 becomes an input variable for the next target variable in the chain, i.e., Y_2. Since the order of the chain is may affect the prediction performance, five fold cross-validation is used to identify the optimal order for the target variables.

4.4. Experiment

In this section, I describe the data collection followed by experiments. Seven baselines are included to study the performance of the proposed DMR framework.

4.4.1. Data collection

I use the results of a financial literacy survey issued to retail superannuation members and provided to me by a leading wealth management business in Australia.

The survey consists of eight financial knowledge questions (Table 4.1), four financial attitude questions (Table 4.2) and four financial behaviour questions (Table 4.3). The survey is complimented by personal and demographic questions which include employment status, income, marital status, household composition and education.

Table 4.1: Financial knowledge questionnaire

Basic Knowledge	Numeracy	Suppose you had $100 in a savings account and the interest rate was 2% per year. After 5 years how much do you think you would have in the account if you left the money to grow…?	93.3% (959)
	Inflation	Imagine that the interest rate on your savings account was 1% per year and inflation was 2% per year. After 1 year, how much would you be able to buy with the money in this account…?	89.3% (918)
	Diversification	Buying a single company's shares usually provides a safer return than a managed fund…?	97.6% (1,003)
	Time value of money	Assume a friend inherits $10,000 today and their sibling inherits $10,000 three years from now. Who is richer because of the inheritance…?	79.3% (815)
Superannuation Knowledge	Concessional tax rate	Before tax (concessional) payments that you or your employer might make into your superannuation fund are taxed at…?	61.9% (636)
	Concessional cap	The annual limit for concessionally taxed payments into your superannuation fund is…?	36.7% (377)
	Non-concessional cap	The three-year limit for after-tax (non-concessional) payments into your superannuation fund is…?	20% (206)
	Super Guarantee rate	The current Superannuation Guarantee rate (that is, the rate of contribution your employer is legislated to pay) is…?	70.7% (727)

Table 4.2: Financial attitude questionnaire

	Entirely disagree	**Mostly disagree**	**Somewhat disagree**	**Neither agree nor disagree**	**Somewhat agree**	**Mostly agree**	**Entirely agree**
Interest in superannuation	3.8% (39)	4.9% (50)	7.3% (75)	28.9% (297)	17.4% (179)	20.2% (208)	17.5% (180)
Value of superannuation for retirement	55.5% (571)	25.8% (265)	9.4% (97)	4.7% (48)	2.8% (29)	0.8% (8)	1% (10)
	Daily	**Weekly**	**Monthly**	**Quarterly**	**6 monthly**	**Annually**	**Never**
Planning and goal setting	9.5% (98)	18.9% (194)	27.1% (279)	18.9% (194)	13.1% (135)	9.2% (95)	3.2% (33)
	Poor	**Not very good**	**Fair**	**Good**	**Very good**	**Excellent**	
Financial knowledge self-assessment	2% (112)	7.1% (233)	22.7% (328)	31.9% (73)	25.4% (21)	10.9% (261)	

Table 4.3: Financial behaviour questionnaire

	Entirely disagree	**Mostly disagree**	**Somewhat disagree**	**Neither agree nor disagree**	**Somewhat agree**	**Mostly agree**	**Entirely agree**
Tracking investment option allocation	4.8% (49)	6% (62)	4.4% (45)	13.9% (143)	5.4% (55)	25.5% (262)	40.1% (412)
Tracking periodic performance	4% (41)	4.8% (49)	5.3% (54)	18.5% (190)	6% (62)	27.2% (280)	34.2% (352)
Tracking account balance	2% (21)	1.8% (18)	2.3% (24)	1.4% (14)	9.1% (94)	22.2% (228)	61.2% (629)
	Daily	**Weekly**	**Monthly**	**Quarterly**	**6 monthly**	**Annually**	**Never**
Engage in conversation about super	1% (10)	4.6% (47)	14.6% (150)	15.2% (156)	16.5% (170)	20.2% (208)	27.9% (287)

Data collected from the financial literacy survey provides independent variables for learning the models for financial literacy.

I train all models against a set of independent variables. The dataset covers both demographic snapshot data and behavioural data. The demographic information is comprised of 24 basic features including customer details, account details and investment allocation. Demographic features are known at account inception and can be applied to new members joining the fund. Behavioural information contains 68 behavioural features for up to 12 months and includes investment allocation maintenance, account maintenance, customer engagement and transactional features.

The behavioural data set is used after account inception, though accuracy greatly improves as data accumulates.

Table 4.4: Training dataset

Variable type	Category	Description	Variable name
Dependent variables			Financial knowledge (2); Financial attitude (4); Financial behaviour (4)
Independent variables	Demographic	Customer details	State; Postcode; CustAge; Gender
		Account details	Acct_Val; AccStmtTranCommPref; AccAnnualRptCommPref; Saving_Plan; FNI_Tran_Acss; FNI_Enq_Acss; CustReturnedEmailFlag; CommunicationReference; NumberOptions; num_accounts; ivst_grup; has_mobile; has_work_tel; has_home_tel
		Investment allocation	Cash; Fixed_interest; Global_fixed_interest; Australian_share; Global_share; Property
	Behavioural	Investment allocation maintenance	Change_12m_Cash; Change_12m_Fixed_interest; Change_12m_Global_fixed_interest; Change_12m_Australian_share; Change_12m_Global_share; Change_12m_Property
		Account maintenance	ADDRESS_CHANGE; Advised_to_Direct; CUST_GIVEN_CHANGE; CUST_NAME_CHANGE; Direct to Direct; Direct_to_Advised; EMAIL_CHANGE; HOME_TEL_CHANGE; MOBILE_CHANGE; NewAdviser; NewDealer; TITLE_CHANGE; WORK_TEL_CHANGE
		Customer engagement	ONLINE_Login; Investor_Call Transfer; Investor_Distribution; Investor_Email; Investor_Face to face; Investor_Inbound; Investor_Internal enquiry; Investor_Investigation; Investor_Outbound; Investor_Platinum Adviser; Non-member_Call Transfer; Non-member_Distribution; Non-member_Email; Non-member_Face to face; Non-member_Inbound; Non-member_Internal enquiry; Non-member_Investigation; Non-member_Outbound; Non-member_Platinum Adviser
		Transaction	ONLINE_Additional Applications; ONLINE_Change Address; ONLINE_New Funded Applications - OAF; ONLINE_RIP Maintenance; ONLINE_Switches; ONLINE_Unfunded Applications - OAF; Personal_conc; Personal_inj; Personal_Non_conc; Rollover; Rollover_wdl; salary_Sacr; Small_Bus_15yr_Ex; Small_Bus_Ret_Ex; Spouse_non_conc; super_guarantee; Switch; Withdrawal; personal_non_conc_amt; personal_conc_amt; salary_sacr_amt; spouse_amt; personal_inj_amt; Small_Bus_Ret_Ex_amt; Small_Bus_15yr_Ex_amt; Gov_co_cont_amt; SG_amt; Total_concessional; Total_non_concessional; concessional_cap

4.4.2. Experimental setup

Evaluation Protocols

In this study, the model and the baselines are evaluated using Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), which are the two standard evaluation metrics used in the literature. To be specific, let $D_s = \{(\boldsymbol{x}_1, \boldsymbol{y}_1), (\boldsymbol{x}_2, \boldsymbol{y}_2), \ldots, (\boldsymbol{x}_n, \boldsymbol{y}_n)\}$ denote the data set, the evaluation metrics are defined as:

$$\mathrm{RMSE} = \sqrt{\frac{1}{|D_s|}\sum_{i=0}^{|D_s|}(\boldsymbol{y}_i - \widehat{\boldsymbol{y}}_i)^2}$$

$$\mathrm{MAE} = \frac{1}{|D_s|}\sum_{i=0}^{|D_s|}|\boldsymbol{y}_i - \widehat{\boldsymbol{y}}_i|$$

where $\widehat{\boldsymbol{y}}_i$ is the predicted values for all target variables, and all operations are point-wise the multi-output task.

Baselines

To study the performance of the proposed DMR framework, I selected seven baselines, including inherent multi-output learning algorithms and wrapper algorithms.

- **Ridge** (Tikhonov and Arsenin, 1977) is a linear model with L2 regularization that significantly reduces the risk of overfitting for ill-posed problems.
- **Lasso** (Least Absolute Shrinkage and Selection Operator) (Tibshirani, 1996) is a linear model with L1 regularization that is more likely to result in a sparse solution than Ridge, and hence relies on fewer features.
- **Elastic Net** (Zou and Hastie, 2005) is a linear model with combined L1 and L2 regularization, offering a compromise between Ridge and Lasso.

- **k-NN** regression is a non-parametric method that does not require assumptions on the data distribution, and hence is adaptive to the data.
- **DTR** (Decision Tree Regressor) is a popular machine learning algorithm that makes decisions based on tree structures, which mimics the decision-making mechanism used by humans.
- **XGB-W** (XGBoost regressor within a multi-output wrapper) (Chen and Guestrin, 2016) is a decision tree-based ensemble learning algorithm under the gradient boosting framework. It represents the state-of-the-art performance of supervised learning.
- **XGB-C** (XGBoost regressor within a multi-output chain) is similar to XGB-W but implemented with a multi-output chain.
- **DMR** (Debiased Multi-output Regression) is the proposed framework which combines the debiasing method with an underlying XGBoost regressor.

Experiment Results

The performance comparison results on the financial literacy prediction task are shown in Table 4.5 and Table 4.6. For all target variables, DMR has achieved the best MAE and RMSE scores. However, the improvements over the state-of-the-art XGB models are different for different target variables. For example, on both the RMSE and MAE metrics, the DMR and XGB models have very close error values on the target variables “Super_knowledge” and “A_interest”, whereas DMR gives a considerably better result on the target variable “Basic_knowledge”. This difference is a result of the debiasing process, or in other words, there are more non-response bias related to “Basic_knowledge” than “Super_knowledge”. In summary, the results showed that the proposed DMR model can boost the performance of multi-output regression tasks, especially when some target variables surfer from non-response bias.

Table 4.5: Comparison results on the RMSE metric.

	Basic_knowledge	Super_knowledge	A_interest	A_belief	A_think_about	A_self_assess	B_know_balance	B_know_options	B_know_performance	B_talk_about
Ridge	4.5459	8.8132	6.8301	6.6545	7.6063	6.2645	9.5440	9.7384	11.5744	13.1847
Lasso	1.6568	4.3288	4.1593	2.7058	6.0949	2.7029	2.7256	4.1505	5.5465	6.4924
EN	1.8099	5.5616	6.1677	3.6232	7.6421	3.6928	4.1728	5.0391	6.8390	8.8911
K-nn	0.8961	1.3714	1.6935	1.2900	1.6633	1.2622	1.4151	1.9169	1.7872	1.7748
DTR	1.1347	1.6732	2.0844	1.6999	1.9164	1.5236	1.7378	2.3587	2.1783	2.2284
XGB-W	0.8952	1.2883	1.6476	1.3395	1.5018	1.2144	1.3869	1.8266	1.7433	1.7296
XGB-C	0.8952	1.2936	1.6553	1.3157	1.5009	1.2034	1.3621	1.8327	1.7829	1.7305
DMR	**0.8747**	**1.2853**	**1.6371**	**1.2980**	**1.4929**	**1.1901**	**1.3316**	**1.7966**	**1.7354**	**1.7103**

Table 4.6: Comparison results on the MAE metric.

	Basic_knowledge	Super_knowledge	A_interest	A_belief	A_think_about	A_self_assess	B_know_balance	B_know_options	B_know_performance	B_talk_about
Ridge	0.8621	1.4671	1.5702	1.2251	1.5718	1.2401	1.3321	1.8286	1.8086	2.0560
Lasso	0.7121	1.2212	1.4528	0.9779	1.4467	1.0153	0.9701	1.5176	1.5054	1.6867
EN	0.7275	1.2920	1.5638	1.0245	1.5267	1.0824	1.0417	1.5818	1.5704	1.8118
K-nn	0.6819	1.1365	1.3757	0.9317	1.3527	1.0106	0.9749	1.4883	1.3752	1.4800
DTR	0.7264	1.3089	1.5983	1.1159	1.4796	1.1633	1.0134	1.6507	1.5625	1.7409
XGB-W	0.6701	1.0528	1.3102	0.9735	1.1990	0.9741	0.9220	1.3932	1.3323	1.4284
XGB-C	0.6701	1.0573	1.3204	0.9643	1.1992	0.9668	0.8707	1.3560	1.3430	1.4156
DMR	**0.6454**	**1.0440**	**1.3009**	**0.9490**	**1.1930**	**0.9512**	**0.8465**	**1.3295**	**1.3085**	**1.3981**

4.5. Discussions

The ongoing measurement of financial literacy represents several notable opportunities for a superannuation and investments trustee. First, in exercising the role of trustee, superannuation funds have a responsibility to ensure the financial wellbeing of members. Targeted marketing and education can be tailored to members based on their financial literacy. Supporting members who choose to seek financial advice. Identification of vulnerable members. Superannuation funds have a role as trustees to maximize the outcomes of their membership base. The context specific measurement for financial literacy allows me to predict positive financial outcomes of members, and those who may make mistakes.

As a prediction framework with commercial applications it is important to ensure that the model developed for superannuation literacy is maintained as the true feature coefficients change over time. Chapter 3 provides an elaboration of the challenges associated with the ongoing collection of financial literacy data through online surveys. Therefore, a benchmark against which to assess model performance is difficult to ascertain. As a result, financial outcomes are proposed as the source of truth with which to measure model shift. The relationship between real and predicted financial outcomes provides a benchmark against which model performance will be evaluated, and retraining triggered by a predetermined threshold as determined by the commercial entity.

To assess variable importance, I observe the mean decrease in accuracy by MSE for each of the model variables. Since I have 10 chained models in the prediction framework I use voting to consolidate variable importance into a single vector. Table 4.7 reports the top 20 variables and the associated average percent increase in mean square error.

Table 4.7: Aggregate variable importance

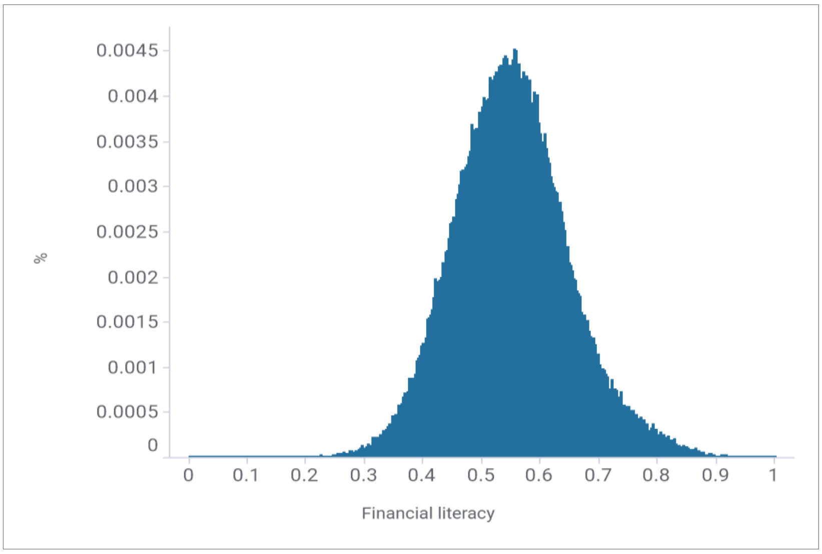
Model variable	**Avg Inc%MSE**
FNILogin	0.035777
Global_fixed_interest	0.017841
CustAge	0.014800
Fixed_interest	0.016971
Change_12m_Australian_share	0.015117
Property	0.013704
Acct_Val	0.013575
concessional_cap	0.013174
Change_12m_Global_fixed_interest	0.012841
SG_amt	0.013585
Australian_share	0.012472
Change_12m_Fixed_interest	0.012549
Change_12m_Global_share	0.011731
Change_12m_Property	0.011970
Investor_Call	0.018102
Rollover_wdl	0.017233
NumberOptions	0.011347
Withdrawal	0.012786

Advised_to_Direct	0.013427
Investor_Outbound	0.015699

A review of variable importance indicates that the most important variables can be defined as those which describe the extent to which superannuation members engage with the fund provider and the product itself. Overall online engagement is the most important variable in the prediction framework. Nine of the top 20 reported variables involve asset allocation, and the maintenance of asset allocation over a 12 month observation window. Customer age and account balance are also reported as important variables in the prediction of financial literacy.

To represent financial literacy as a single and meaningful measure I aggregate the 10 predictions in the financial literacy framework. I combine the financial literacy measure on the following assumptions; the relative value of each measure is not expected to be equal and; not all metrics are expected to be positively correlated with high financial literacy (such as the belief that superannuation isn't important for retirement wellbeing) thus a negative weighting may be appropriate. To address these challenges I optimise the weights of each prediction by the observed financial outcomes for each customer portfolio over 12 months. For the purpose of this chapter I use portfolio return, portfolio volatility and account balance as proxies for positive financial outcomes. I standardise and combine the outcome variables and train a simple linear regression while controlling for customer age. The model achieves an adjusted R-square of 84.64% and the resulting Pearson correlation coefficients for portfolio return, portfolio volatility and account balance are 0.407675, 0.39239 and 0.290981 respectively. By contrast, the accepted measure for financial literacy, basic knowledge, has corresponding Pearson correlation coefficients of 0.131159, 0.134412 and 0.131924 for portfolio return, portfolio volatility and account balance respectively.

Figure 4.1: Histogram and summary statistics – predicted financial literacy



Mean	0.54979
Std.Dev	0.09717
Min	0.00000
Median	0.54650
Max	1.00000
Skewness	0.25478
Kurtosis	0.34894
N	225,610

The resulting financial literacy metric is estimated for the full 225,000 retail members in this study. The scores range between 0 and 1, with an average financial literacy of 55% and standard deviation of 9.7% (Figure 4.1). The results shows a positive linear relationship between the financial literacy measure and average return and average account balance (Table 4.8).

Table 4.8: Avg. balance and return by financial literacy score

Level	Range	N	Avg. balance	Avg. return
Low	0.0 - 0.4	11,834	$ 79,826.83	4.7%
Medium	0.4 - 0.5	57,579	$ 93,296.67	5.3%
	0.5 - 0.6	92,007	$ 118,353.85	6.1%
	0.6 - 0.7	49,405	$ 126,501.50	7.2%
High	0.7 - 1.0	14,785	$ 133,178.49	8.5%

4.6. Conclusion

Financial literacy is a complex and multifaceted construct used to aggregate and describe financial decision making in individuals. Past research has been challenged to develop a meaningful passive measurement construct for financial literacy which is predictive of positive financial outcomes. Survey bias and access to vast quantities of administrative data have largely hindered past efforts to address these challenges. In this chapter I bring together data mining technology with administrative data from one of Australia's leading superannuation funds to introduce a novel solution for predicting financial literacy in superannuation.

The findings of this chapter provide a framework for superfund trustees to predict the decision making abilities of their members. This research would benefit from a prescriptive analysis of the important variables in this framework to identify how best to elevate member financial literacy and retirement well-being.

5. Modelling unseen churn using sequential pattern features

In the previous chapters I have presented an effective measurement construct and prediction framework for financial literacy in superannuation. In this chapter I integrate this framework with a novel solution for a real world business problem, customer churn. Through this chapter I demonstrate the relationship between customer churn and financial literacy. The results of this analysis indicate that financially sophisticated investors are more discerning with respect to product selection, providing guidance for the design and management of future product offerings.

The role of churn modelling is to maximize the value of marketing dollars spent and minimize the attrition of valuable customers. While it is widely accepted to be more cost effective to retain customers than to acquire new ones, there is very little evidence to support that any wealth management business in Australia has utilized customer churn prediction as part of a customer relationship management framework. Though churn prediction is a common classification task, traditional approaches cannot be employed directly due to the unique issues inherent within the wealth management industry. Through this chapter I address the issue of unseen churn in superannuation; whereby customer accounts become dormant following the discontinuation of compulsory employer contributions, and suggest solutions to the problem of scarce customer engagement data. To address these issues, this chapter proposes a new approach for churn prediction and its application in the superannuation industry. I use the extreme gradient boosting algorithm coupled with contrast sequential pattern mining to extract behaviours preceding a churn event. The results demonstrate a significant lift in the performance of prediction models when pattern features are used in combination with demographic and account features.

5.1. Introduction

Churn modelling is one of the most common applications for machine learning in industry and forms a key component of any effective customer relationship management framework (Ballings & Van den Poel, 2012). Due to intense competition and the high costs associated with new customer acquisition, many businesses are looking to machine learning to guide customer retention strategy (Popovic & Basic, 2009; Ali & Ariturk, 2014, Xie et al., 2009). While there is no commonly accepted definition for customer churn it is generally understood as the termination of a financial relationship between a customer and a business (Popovic & Basic, 2009). Churn prediction refers to the statistical and computational processes used to derive expectations from historical customer data about the state of a customer relationship at a specified time in the future. Churn prediction is an important part of customer relationship management since it allows businesses to prioritize relationships and marketing spend to entice the most risky customers to stay with their brand or service (Chu et al., 2016).

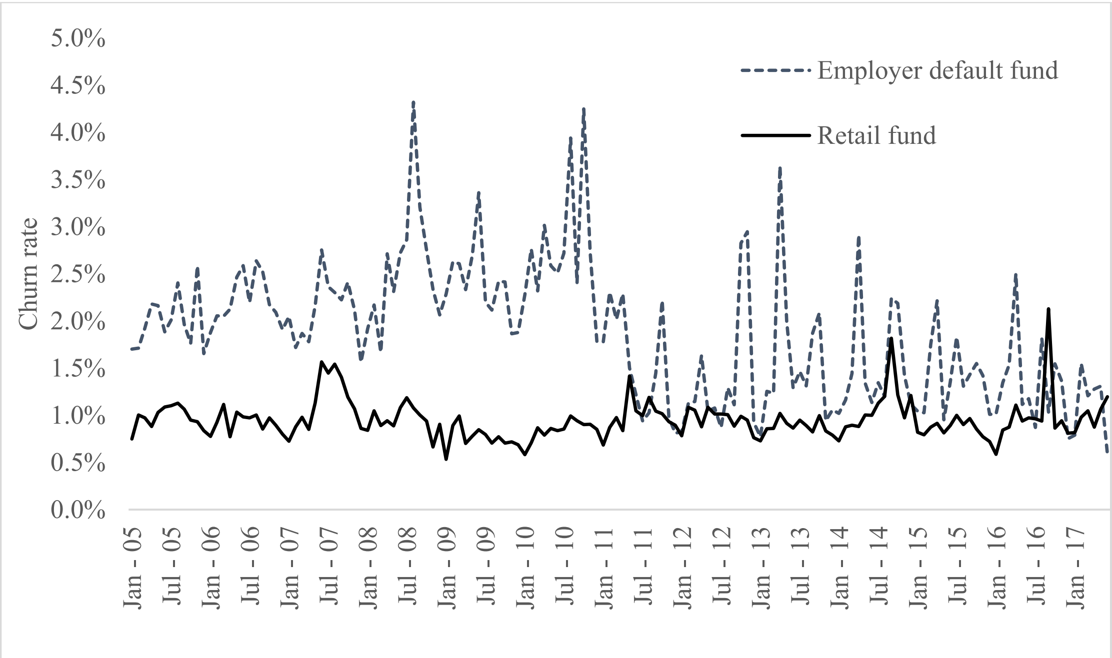
In the past, customer retention programs utilized by the superannuation industry have relied heavily on descriptive statistics and domain knowledge. Historical attrition rates are used to guide decision making with respect to customer campaigning and relationship management. Customer segment groups with higher than system attrition are identified as at-risk and subsequently engaged through customer campaigning. Prioritization of customer relationships is ineffective in driving positive return on investment for marketing spend and there is limited evidence to suggest that advanced approaches to data mining have been utilized effectively to drive business benefits.

The Australian superannuation industry represents a unique set of challenges and opportunities for customer churn prediction. Research indicates that few Australians have an adequate understanding of the basic principles of superannuation (Agnew, Bateman & Thorpe, 2013). Despite this, the majority of the nation's current and retired workforce hold superannuation as their most valuable asset, second only to the family home. This paradigm, whereby participants in the system have a limited knowledge of how it works, has come about due to the obligatory participation in superannuation through compulsory employer contributions. As a result, legislation has evolved to allow apathetic customers to defer by default the decision making process for their superannuation up until retirement (Gallery, Newton & Palm, 2011).

This means that customer engagement data is scarce, and represents a substantial challenge to super funds looking to understand their customers through customer engagement data.

The tendency for Australians to default to employer funds means that many accrue multiple super accounts during their working lives. This proliferation of apathy has seen the balance of lost super funds climb to $8.45bn and 496k accounts nationally (APRA, 2016). The result is two-fold, while customer churn is high (as represented by Fig. 1.) industry data indicates that a proportion of open accounts are dormant and will inevitably become lost. These accounts represent unseen churn and are not captured using conventional approaches.

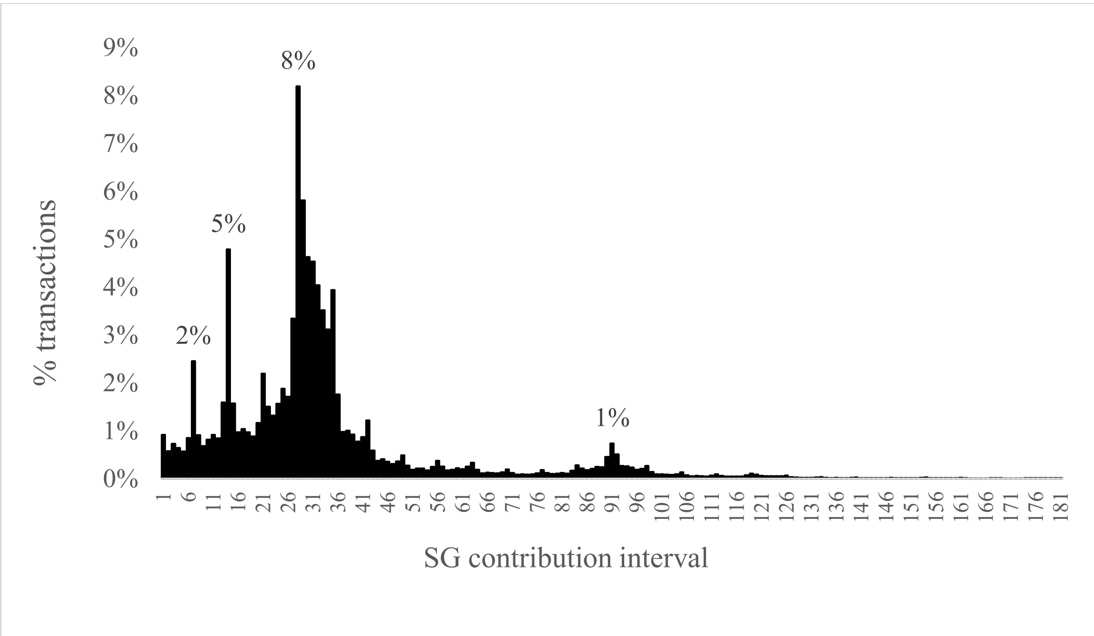
Figure 5.1: Monthly customer churn rates



Due to the heavily mandated nature of superannuation, employers are compelled to make compulsory super guarantee (SG) contributions on a regular basis. The regularity of SG contributions means that they are highly predictable, and follow strongly time dependent patterns. Figure 5.2 below depicts this time dependency and illustrates that spikes occur at 7, 14, 28 and 30 days, corresponding with weekly and monthly patterns.

Through this chapter I find that the existing approach to customer retention and churn prediction in unable to appropriately address the challenges (scarce engagement data and unseen churn) and opportunities (predictable contribution patterns) for the superannuation industry. I propose a solution using machine learning which adopts a definition for customer churn which addresses the issue of unseen churn. I build intermediary features at scale to uncover previously hidden customer engagement data. Finally I use an advanced pattern mining technique to discover predictable contribution patterns. Through this research I demonstrate how churn prediction can be enhanced through the application of advanced pattern mining techniques.

Figure 5.2: Super guarantee contribution intervals



The remainder of this chapter is organized as follows. Section 2 reviews relevant and related work. Section 3 discusses the problem statement. In section 4 I describe the predictive framework. Section 5 provides an overview and discussion of the results, and section 6 concludes.

5.2. Related work

5.2.1. Customer Churn Prediction

There is a substantial body of research for churn prediction. Examples of customer churn prediction are common in industries such as telecommunications (Huang et al., 2015; Idris, Rizwan & Khan, 2012), multimedia (Coussement & De Bock, 2013; Tsai & Chen, 2010) and retail banking (Popovic & Basic, 2009, Ali & Ariturk, 2014). Past research has focused primarily on issues and developments in the area of machine learning algorithms (Popovic & Basic, 2009, Coussement & De Bock, 2013; Tsai & Chen, 2010, Burez & Van Den Poel, 2009; Idris, Rizwan & Khan, 2012), sampling techniques (Burez & Van Den Poel, 2009; Idris, Rizwan & Khan, 2012, Xie et al., 2009) and feature engineering (Ali & Ariturk, 2014).

Research highlights a great diversity of machine learning algorithms for churn prediction. Among these, random forests, support vector machines, neural networks, logistic regression and decision trees feature most prominently (Huang et al., 2015; Xie et al., 2009). A long history of customer churn prediction has seen substantial advancement against classical approaches such as RFM indexes (recency, frequency, monetary value) (Ballings & Van den Poel, 2012). While there is some disagreement around which machine learning algorithms are superior, recent work indicates that the random forest algorithm provides the best results (Huang et al., 2015; Coussement & De Bock, 2013).

Recent work has focused on class imbalance for churn prediction. This is especially pertinent to users of tree based algorithms, where research finds a bias towards the majority class (Burez & Van Den Poel, 2009). There are 3 broad approaches to handling class imbalance; down-sampling, up-sampling and weighted learners. While recent research supports the use of weighted learners (Huang et al., 2015), Burez and Van den Poel (2009) find that advanced sampling techniques do not exceed the performance of under-sampling when evaluated by AUC.

Despite a diversity of applications for customer churn prediction, there is limited evidence to indicate that churn prediction has been used within the Australian superannuation industry. Chu et al. (2016) cite the use of a random forest algorithm for customer churn in superannuation and pension products at a leading Australian fund. They report enhanced performance through the adoption of a random forest algorithm, and compare this to logistic regression, Naïve Bayes and support vector machines. The paper provides very little detail on the predictive framework used and rather, focuses on a business integration problem for predictive analytics. To my knowledge, this chapter is the first to deeply articulate a predictive modelling framework for customer churn in the Australian superannuation industry.

5.2.2. Contrast Sequential Pattern Mining

Contrast sequential pattern mining is useful for predicting patterns in ordered events while contrasting against multiple classes (Zheng et al., 2016). While sequential pattern mining is shown to be effective for prediction it is unable to solve for a classification problem.

CSP is a variation of sequential pattern mining. Where sequential pattern mining builds evaluation metrics (support and confidence) against an itemset (Wright et al., 2015), CSP does so independently for positive and negative classes (Zheng et al., 2016). CSP is therefore complementary to classification problems.

Given a dataset $\boldsymbol{D}$ containing a list of sequences $\boldsymbol{s_i}$, sequences are contrast by a binary class variable $\boldsymbol{c}$. A sequence is an ordered list of items $\boldsymbol{i_k}$. The list of permissible items within a sequence are described as events $\boldsymbol{e_j}$.

An implementation of eCSP uses a minimum support expressed as *min_sup,* and minimum contrast ratio *min_CR* to filter outliers and statistical anomalies from the list of contrast sequential patterns. Support is calculated as the count of sequences for like classes, where;

$$\sup(s_1, c_1) = \ N_{s=1,c=1}$$

Then, the contrast rate is calculated per sequence s_i, expressed as;

$$CR_i = \frac{\sup(s_i, c_1)}{\sup(s_i, c_2)}$$

Using support and contrast rates, the eCSP algorithm performs a search for sequences and sub-sequences using CSP-tress to identify patterns which meet the prescribed rules for inclusion i.e *min_sup, min_CR*. A basic implementation of this algorithm is given by Zheng et al. (2015) and represented in figure 5.3.

Figure 5.3: Pseudocode for eCSP implementation (Zheng et al., 2015)

```
Algorithm 1 RunCSP
Input: SequenceDatabase database, min_cr, max_length
Map<Prefix,Set<Integer>> mapSeqID=findFrequentItems(database);
for Entry entry : mapSeqID.entrySet() do
    if entry.getValue().size() >= min_sup then
        Prefix pref = entry.getKey();
        projectDB = buildProjectDB(pref, database);
        if (CR(pref)>min_cr) then
            //found and output a CSP
    if pref.sup1==0 || pref.sup2==0 then
        continue; //don't need go deeper
    Recursion(pref, 2, projDB);
```

```
Algorithm 2 Recursion
Input: pref, level, projectDB
Set<Pair> pairs=findAllFrequentPairs(prefix, projectDB);
for Pair p : pairs do
    Prefix pref2 = getNewPrefix(pref, p.pref);
    ProjectDB pDB2=buildProjectDB(p.item, projectDB, p.isPostfix);
    if CR(pref)>min_cr then
        //found and output a CSP;
    if p.sup1==0||p.sup2==0 then
        continue;
    if Prune==true then
        continue;
    if k<max_len then
        Recursion(pref2, level + 1, pDB2);
```

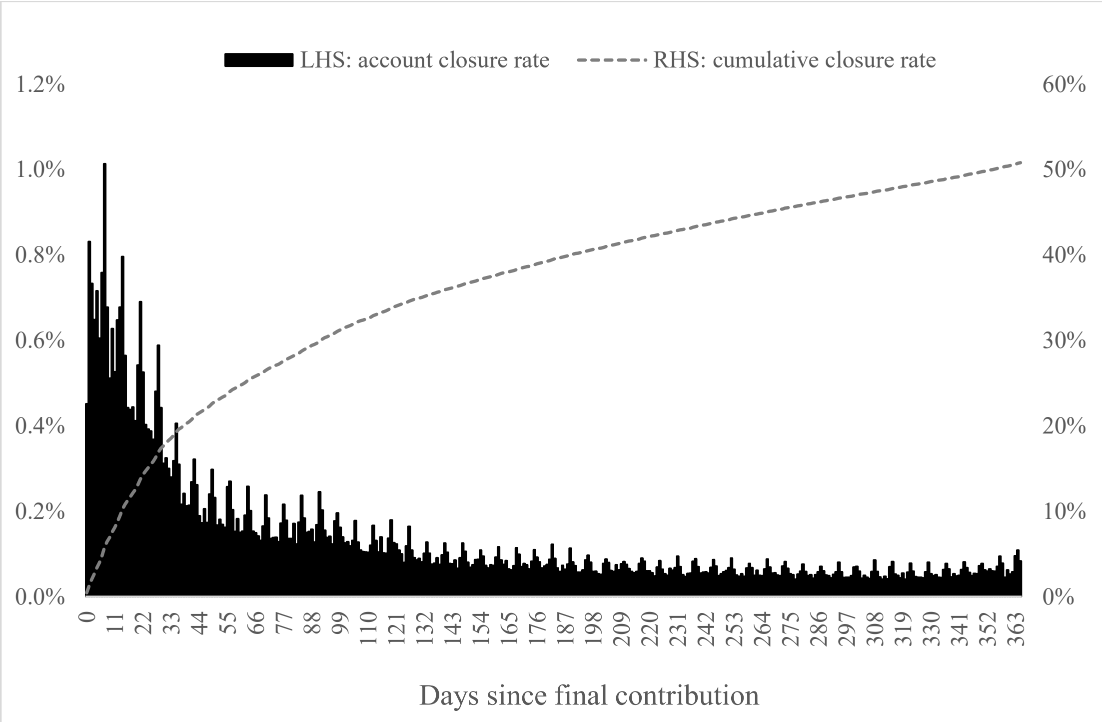
5.3. Problem Statement

This chapter presents a special case of churn prediction for a leading Australian superannuation fund.

For many Australians, superannuation exists solely as a vehicle for the accumulation of employer super guarantee contributions. While the cessation of super guarantee is often a precursor to a churn event, empirical evidence suggests that many accounts remain open and inactive for extended periods of time following a final employer contribution (Figure 5.3 illustrates this point, where 49% of accounts remain open after 12 months of inactivity). Often, by the time there is sufficient evidence to predict a likely account closure the customer relationship has already ended. As a result, traditional churn prediction has limited effectiveness in making timely and actionable predictions for customer churn management.

To address this issue I build a prediction model for super guarantee attrition. In this approach I expose patterns in employer contributions and surface evidence for attrition through the behaviours of investors and their financial advisers. By predicting the cessation of an ongoing employer contribution stream it is found that prediction outcomes are timely, relevant and actionable. The model presented in this chapter recognizes contributions as they arrive and, based on a number of factors, predicts the likelihood that it will be the member's last contribution. If the evidence for super guarantee attrition is compelling, the business is able to take immediate action to retain the customer.

Figure 5.4: Account churn by days since last contribution



A binary label variable is built using a 6 month observation window. Where an account has not received a super guarantee contribution within the observation window it is deemed to have lapsed and the label variable is given a value of 1. Alternatively, super guarantee is ongoing and the label variable receives a value of 0.

5.4. Prediction Framework

Churn prediction models were developed using multiple algorithms and trained on 447 features and one binary label variable. The training data is built on 284,762 retail, employer default and employer retained superannuation accounts. Only accounts which have recently received (within 6 months) a super guarantee contribution are included in the final training data set. The prediction outcome provides a measure of probability for an account not receiving an SG contribution in the following 6 months.

5.4.1. Classifier

Multiple classification algorithms are used for comparison; a decision tree, random forest (Breiman, 2001) and extreme gradient boosting (XGBoost) (Chen & Guestrin, 2016). All models share their tree based structure however each has unique merits. A decision tree is a simple model and allows for the extraction of business rules. Decision trees are however at risk of overfitting without appropriate testing and pruning against a test dataset. Random forests on the other hand do generalize well as an outcome of the bagging function. Furthermore, the use of the random forest algorithm is supported by research (Huang et al., 2015; Phua et al., 2012; Coussement & Van den Poel, 2008) where it is demonstrated to perform marginally better by AUC than other classifiers tested. Random forests do not allow users to visually review the decision tree and are therefore less interpretable. Extreme gradient boosting also suffers from diminished interpretability relative to the decision tree however has been shown to perform very well for a variety of classification tasks (Chen & Guestrin, 2016).

While it is important to test a variety of algorithms to maximize results for a given classification problem research suggests that many common classifiers can achieve comparable performance, and that gains in predictive performance are achieved through superior feature engineering (Huang, 2015). As a result, the focus of this research is the development of meaning features.

5.4.2. Designing Static and Sequential Features

In total, 447 demographic, financial, transactional and behavioral features are built for training and used for super guarantee churn prediction.

The aforementioned scarcity of customer engagement data represents a significant challenge to wealth management businesses looking to better understand their customers through engagement data. The highly intermediated nature of superannuation in Australia however represents a substantial opportunity to combat this shortage of customer data. Intermediaries, including financial advisers, licensees and employers, all play a role in managing customer accounts. The interactions these agents have with a super fund can be very insightful in understanding a customer. Once aggregated at the intermediary level, these features can expose trends in customer behavior and intermediary policy.

The following feature groups are representative of the training set:

1. **Customer.** Customer features include demographic variables such as age, gender, race, marital status and socio-economic segment.
2. **Intermediary.** Intermediary variables include interactions data for agents and aggregated customer and account variables. These variables serve to provide insight into trends at the agent level and expose agent initiated churn.
3. **Account.** Account level features include variables around product, investment and asset class selection, valuation and insurance. Account features are enriched with data around additional financial holdings such as home loans, credit cards and savings accounts.
4. **Engagement.** Engagement data comes from multiple CRM systems and databases. Engagement features include information around contact center enquires and online banking activities.
5. **Financial.** Financial features include all transactional level variables. Examples of financial features include asset switching, withdrawals, contributions, fees, premiums and derived features from this data. Numerous features were created to expose contribution patterns within member accounts and generate flags where those patterns are violated.
6. **Sequential patterns.** Strings of sequential patterns bringing together financial and engagement data were created and captured all interactions for a 6 month period. Sequential pattern features include all active and passive customer and account events. I used an implementation of contrast sequential pattern mining as described by Zheng et al. (2016) and applied a cut-off contrast rate of 2.

Figure 5.5: Data processing flow

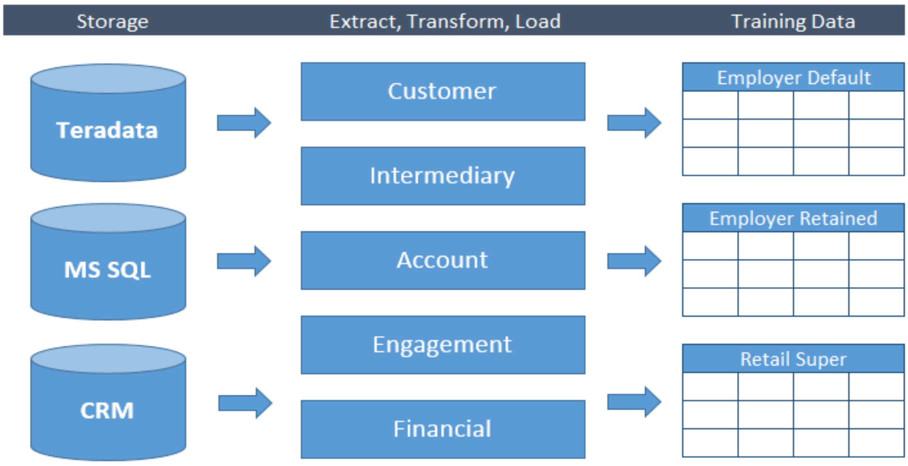
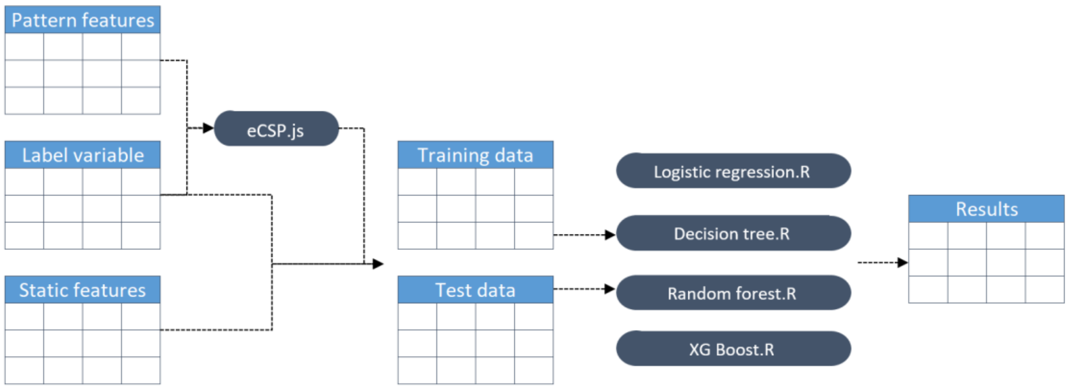


Figure 5.6: Prediction framework



5.5.Results and Discussion

5.5.1. Data Collection

Final data cleansing and segmentation was carried out to improve model performance and avoid erroneous results.

Missing observations were imputed with appropriate values. For missing character variables a value of *NULL* replaced blank cells. Missing dates and timespans were given a date of *01/01/9999*. This ensures that the results for these observations are distinctly different while allowing derived variables to continue functioning. Missing numerical variables were given a value of *0*.

The imputed data table was split by product group; Employer Default, Employer Retained and Retail Super. Employer Default accounts are originated by a business who own an employer plan. They are the default option for employees who choose not to exercise super choice. Employer Retained accounts are those which have previously been associated with an employer default account and have since stopped working with the employer. When this relationship ends the members account is migrated to an employer retained account, and the employer no longer has administrative privileges over the account. The final product group, Retail Super, is open to the public and is commonly originated by a customer in consultation with a financial adviser. Since retail super accounts are most often opened as part of a financial advice strategy, they represent the lowest level of churn risk. The segmentation of data by product group is necessary to address a practical consideration for machine learning. Employer features are not applicable to the retail customer base and as such, it makes sense to separate datasets with distinctly different features. Further, due to the nature of the employer retained product, these members represent a distinctly different customer base and are modelled as such.

Table 5.1 Training dataset

ID
acc_ID,
Label variable
Target,
Feature variables
acct_type, ivst_grup, age, Gender, Channel, open_days, balance, NumberOptions, num_accounts, block_flag, has_email, has_mobile, has_work_tel, has_home_tel, has_adviser, FNI_Tran_Acss, FNI_Enq_Acss, st_pref, rpt_pref, invstor_pref, Returned_Mail_Count, days_no_SG, days_no_personal_contr, days_no_salary_sacr, days_no_spouse_contr, sg_flags, sg_total_amount, sg_times, sg_max_interval, sg_median_interval, sg_last_interval, sg_no_days_exceed_max, sg_no_days_exceed_median, sg_no_days_exceed_last, address_change, adviser_status_change, email_change, home_tel_change, WORK_tel_change, MOBILE_change, dealer_change_times, adviser_change_times, saving_plan_change, fni_tran_acess_change, fni_enq_acess_change, statement_comm_pref_change, investor_comm_pref_change, return_mail_flag_change, annual_rpt_pref_change, employer_id_change, block_code_change, option_number_change, option_number_decreased_flag, option_number_increased_flag, rb_flag_change, balance_change, balance_change_ratio, num_accounts_increased, num_accounts_decreased, call_times, call_flags, adviser_call_times, insurance_times, insurance_flags, login_times, login_flags, switch_times, switch_flags, dealer_mean_super_balance, dealer_median_int_last, dealer_median_int_max, dealer_median_int_med, dealer_num_balance_decline,

dealer_num_balance_increased, dealer_num_exceed_last_int, dealer_num_exceed_max_int, dealer_num_exceed_median_int, dealer_num_first_sg_exist, dealer_num_first_sg_new, dealer_num_no_sg, dealer_num_stop_SG, dealer_num_supers, dealer_ratio_balance_decline, dealer_ratio_balance_increased, dealer_ratio_exceed_last_int, dealer_ratio_exceed_max_int, dealer_ratio_exceed_median_int, dealer_ratio_first_SG_exist, dealer_ratio_first_SG_new, dealer_ratio_no_sg, dealer_ratio_stop_SG, dealer_ratio_super_balance, dealer_ratio_supers, adviser_mean_super_balance, adviser_median_int_last, adviser_median_int_max, adviser_median_int_med, adviser_num_accounts, adviser_num_balance_decline, adviser_num_balance_increased, adviser_num_exceed_last_int, adviser_num_exceed_max_int, adviser_num_exceed_median_int, adviser_num_first_sg_exist, adviser_num_first_sg_new, adviser_num_no_sg, adviser_num_stop_SG, adviser_num_supers, adviser_ratio_balance_decline, adviser_ratio_balance_increased, adviser_ratio_exceed_last_int, adviser_ratio_exceed_max_int, adviser_ratio_exceed_median_int, adviser_ratio_first_SG_exist, adviser_ratio_first_SG_new, adviser_ratio_no_sg, adviser_ratio_stop_SG, adviser_ratio_super_balance, adviser_ratio_supers, adviser_super_balance, adviser_total_balance, area_mean_super_balance, area_median_int_last, area_median_int_max, area_median_int_med, area_num_balance_decline, area_num_balance_increased, area_num_exceed_last_int, area_num_exceed_max_int, area_num_exceed_median_int, area_num_first_sg_exist, area_num_first_sg_new, area_num_no_sg, area_num_stop_SG, area_num_supers, area_ratio_balance_decline, area_ratio_balance_increased, area_ratio_exceed_last_int, area_ratio_exceed_max_int, area_ratio_exceed_median_int, area_ratio_first_SG_exist, area_ratio_first_SG_new, area_ratio_no_sg, area_ratio_stop_SG, area_ratio_super_balance, area_ratio_supers, employer_mean_super_balance, employer_median_int_last, employer_median_int_max, employer_median_int_med, employer_num_balance_decline, employer_num_balance_increased, employer_num_exceed_last_int, employer_num_exceed_max_int, employer_num_exceed_median_int, employer_num_first_sg_exist, employer_num_first_sg_new, employer_num_no_sg, employer_num_stop_SG, employer_num_supers, employer_ratio_balance_decline, employer_ratio_balance_increased, employer_ratio_exceed_last_int, employer_ratio_exceed_max_int, employer_ratio_exceed_median_int, employer_ratio_first_SG_exist, employer_ratio_first_SG_new, employer_ratio_no_sg, employer_ratio_stop_SG, employer_ratio_super_balance, employer_ratio_supers, fund_perf_decreased_flag, fund_performance, fund_worse_flag, additional_application_flags, additional_application_times, new_application_flags, new_application_times, unfunded_application_flags, unfunded_application_times, p1, p2, p3, p4, p5, p6, p7, p8, p9, p10, p11, p12, p13, p14, p15, p16, p17, p18, p19, p20, p21, p22, p23, p24, p25, p26, p27, p28, p29, p30, p31, p32, p33, p34, p35, p36, p37, p38, p39, p40, p41, p42, p43, p44, p45, p46, p47, p48, p49, p50, p51, p52, p53, p54, p55, p56, p57, p58, p59, p60, p61, p62, p63, p64, p65, p66, p67, p68, p69, p70, p71, p72, p73, p74, p75, p76, p77, p78, p79, p80, p81, p82, p83, p84, p85, p86, p87, p88, p89, p90, p91, p92, p93, p94, p95, p96, p97, p98, p99, p100, p101, p102, p103, p104, p105, p106, p107, p108, p109, p110, p111, p112, p113, p114, p115, p116, p117, p118, p119, p120, p121, p122, p123, p124, p125, p126, p127, p128, p129, p130, p131, p132, p133, p134, p135, p136, p137, p138, p139, p140, p141, p142, p143, p144, p145, p146, p147, p148, p149, p150, p151, p152, p153, p154, p155, p156, p157, p158, p159, p160, p161, p162, p163, p164, p165, p166, p167, p168, p169, p170, p171, p172, p173, p174, p175, p176, p177, p178, p179, p180, p181, p182, p183, p184, p185, p186, p187, p188, p189, p190, p191, p192, p193, p194, p195, p196, p197, p198, p199, p200, p201, p202, p203, p204, p205, p206, p207, p208, p209, p210, p211, p212, p213, p214, p215, p216, p217, p218, p219, p220, p221, p222, p223, p224, p225, p226, p227, p228, p229, p230, p231, p232, p233, p234, p235, p236, p237, p238, p239, p240, p241, p242, p243, p244, p245, p246, p247, cust_type1, cust_type2, cust_type3, cust_type4, cust_type5, cust_type6, cust_type7, cust_type8, cust_type9, cust_type10, cust_type11, cust_type12, cust_type13, cust_type14, cust_type15, cust_type16, cust_type17, cust_type18, cust_type19, The resulting three datasets are partitioned at a ratio 80:20 training to test data and down-sampling used to balance the training class labels at a ratio of 1:1. In line with the results of Huang et al. (Huang et al., 2015) I tested weighted instance and down-sampling to address data imbalance. Weights for weighted instance method were calculated to generate a balanced dataset P where w_i is the weight assigned to each observation and $\sum w_i = 1$. N_i is the total number of observations by class, and i is the class designation, taking values of 0 or 1.

$$w_i = \frac{1}{N_i}, \qquad \text{where } \begin{cases} i = 0 \\ i = 1 \end{cases}$$

Under this method the sum of weights for both classes are equal to 1 and balanced. Empirical results showed improved performance when using down-sampling. As a result down-sampling was used for class imbalance.

5.5.2. Evaluation Metrics

Model performance is measured against evaluation metrics recall and AUC. Total recall at the top 20% is used to describe the lift the model generates and is useful in a business setting as it describes the allocative efficiency expected from a given intervention. The definition for recall is below, where R is recall and TP is the number of true positives, given a threshold *t.* I use *t* = 20%.

$$R_t = \frac{\sum TP_t}{\sum TP}$$

Area Under the Curve (AUC) is also used to describe the overall performance of the model. AUC is a useful evaluation metric as it reports performance independent of a cut-off value for classification and is not influenced scaling of the class label Wright et al., 2015). AUC is therefore a less biased measure. AUC is defined below where *i* relates to all data points for *m* when the churn label is 1 and *j* relates to all data points for *n* with churn label 0. p_i and p_j are probabilities assigned to each class and **1** is an indicator function, which is true where the condition $p_i > p_j$ is satisfied.

$$AUC = \frac{1}{mn}\sum_{i=1}^{m}\sum_{j=1}^{n} 1p_i > p_j$$

For benchmarking, a logistic regression is included. In a business setting, interpretability of models is important and findings around the magnitude and direction of influence of features with respect to a label variable are an important input to the development of an effective customer relationship management solution. Improved performance against the logistic regression represents added value from the superior algorithm and is weighed against the cost of diminished interpretability. A decision tree, random forest and gradient boosting (XGBoost) algorithm are used for comparison.

5.5.3. Prediction Performance

The results (Table 5.1) show XGBoost performed strongly against all other methods and overall high predictive performance on the test dataset. Results show that XGBoost outperformed other algorithms by recall, and outperformed by AUC for the employer default and retail super models.

Recall at 20% for the three models; Employer Default, Employer Retained and Retail Super is 86.9%, 71.6% and 80.6% respectively. This indicates that 86.9%, 71.6% and 80.6% of all positive cases are captured within the top 20% of predictions. With recall I can calculate model lift, which represents the improved efficiency against random guess. Model lift for the three models 4.4, 3.6 and 4.0. This means that by selecting the top 20% of predictions I identify 4.4 times more churners than one would by random guess.

I find that the XGBoost algorithm consistently outperforms logistic regression and note limitations of the logistic regression. Tree based algorithms can model more complex relationships and rules perpendicular to the solution space and handle conditions within the data such as heteroscedasticity. As a result, it is evident that logistic regression cannot adequately model the complex relationships between churn and financial data. Furthermore, gradient boosting consistently outperforms decision tree and random forest models by recall in this experiment. Despite marginally higher performance by AUC for the random forest employer retained model I identify gradient boosting as the superior algorithm in all cases. From a practical perspective, recall is a more important statistic for my purposes. The ability to speak to more churners in a smaller sample equates to lower marketing costs and higher retention.

Table 5.2: Model performance

Model	**Classifier**	**AUC**	**Gini**	**Recall @ 20%**
Employer Default	Logistic regression	0.9243	0.8486	81.30%
	Decision tree	0.9265	0.8529	81.73%
	Random forest	0.9393	0.8786	85.00%
	XGBoost	0.9473	0.8945	86.90%
Employer Retained	Logistic regression	0.9143	0.8286	68.50%
	Decision tree	0.9163	0.8326	69.54%
	Random forest	0.9232	0.8464	70.10%
	XGBoost	0.9173	0.8345	71.60%
Retail Super	Logistic regression	0.8874	0.7748	77.40%
	Decision tree	0.8931	0.7861	78.25%
	Random forest	0.9044	0.8088	80.50%
	XGBoost	0.9090	0.8180	80.60%

To objectively assess the impact of pattern features I retrain gradient boosting models with pattern features omitted and report AUC. Results for sequential pattern mining demonstrate the substantial impact pattern features have on model results. The results below (Table 5.2) show that Employer Default model experiences an absolute percentage change in AUC of -9.6% when pattern features are omitted. The Employer Retained model changes by -13.8% and the Retail Super model by -21.8%.

Table 5.3: Sequential pattern results

Model	Classifier	AUC	Gini	Recall @ 20%
Employer Default	XGBoost ex. Pattern Features	0.914	0.828	78.53%
	XGBoost	0.947	0.895	86.90%
Employer Retained	XGBoost ex. Pattern Features	0.869	0.739	61.69%
	XGBoost	0.917	0.835	71.60%
Retail Super	XGBoost ex. Pattern Features	0.827	0.654	63.02%
	XGBoost	0.909	0.818	80.60%

Contrast sequential pattern mining provides several interesting customer insights. On average, I find that a lack of activity provides the most compelling evidence for SG churn. In rare cases however I find strings of events which are highly predictive for SG churn. Events such as customer contact centre enquiries, adviser change, change of address, and logins to the secure online portal are highly indicative of SG churn.

5.5.4. Analysis of Feature Importance

Variable importance reports provide insight into the impact of model features. Table 5.3 below reports the top 10 features by Gini reduction and highlights the importance of features representing contribution timing, customer engagement, sequential patterns and intermediary.

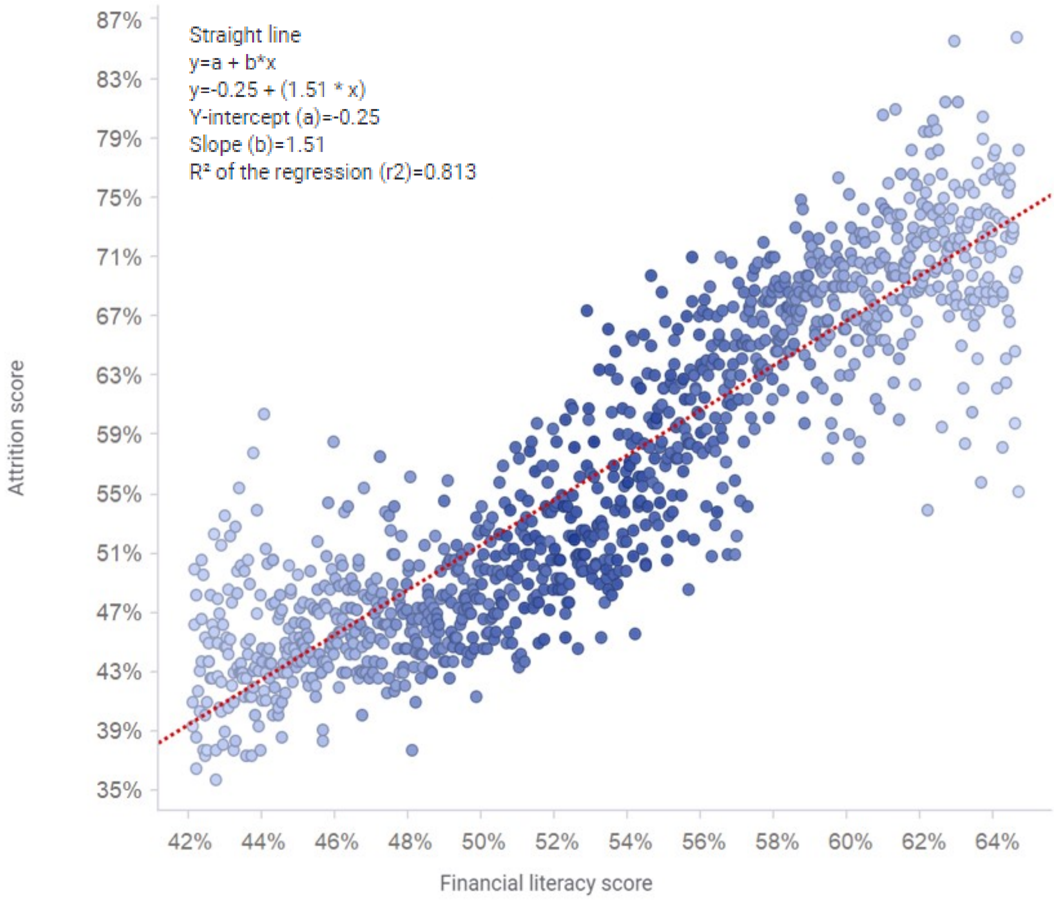
Table 5.4: Variable importance by Gini reduction – top 10

	Employer Default	Employer Retained	Retail Super
1	sg_last_interval	sg_flags	sg_total_amount
2	sg_flags	sg_last_interval	sg_last_interval
3	Age	sg_times	sg_flags
4	balance_change_ratio_6_month	call_flags	sg_median_interval
5	sg_max_interval	days_no_sg	open_days
6	days_no_sg	sg_median_interval	sg_times
7	employer_median_interval_last	balance_change_ratio_6_month	balance_change_ratio_6_month
8	sg_times	balance_change_6_month	balance_change_6_month
9	open_days	sg_total_amount	cba_wealth_band
10	sg_median_interval	call_times	balance

5.6. Churn and financial sophistication

To provide insight into contributing factors associated with account churn, I analyze churn probabilities against the superannuation fund's measure for financial literacy. Superannuation literacy is analyzed using simple linear regression and the results reported. The outcome demonstrates a strong positive relationship between churn and financial sophistication. The coefficient of determination is 0.813, indicating that 81% of the variation in attrition is explained by financial literacy scores. A 1 point increase in financial literacy is associated with a 1.51 point increase in attrition.

Figure 5.7: Attrition score vs. financial literacy score



This result implies that financially literate members are more discerning with respect to product selection and the associated features, and are willing to change fund in order to pursue a more suitable product. This high positive correlation between churn and financial literacy is expected, where numerous studies have shown that financially literate individuals demonstrate superior decision-making abilities with respect to the selection and management of financial products.

In the future, Colonial First State should pair financial literacy results with exit survey feedback to understand the service and product features which are most important to their members.

5.7. Conclusion

This chapter presents a real world application of churn prediction in a leading Australian superannuation fund. With an understanding of the superannuation industry and its participants, I recognize several unique challenges to the industry. I identify issues related to unseen churn and scarce customer engagement data. To address the issue of unseen churn I focus on the underlying driver for account churn and design a label variable for this, super guarantee churn. To address the scarcity of customer engagement data, I build intermediary features to capture interactions from administrative agents of superannuation accounts. Through modelling results I find the XG Boost algorithm with under-sampling is superior to other techniques tested. Variable importance reports indicate that intermediary, pattern and time dependent features make a significant contribution to the predictive performance of the models. Side by side models with and without pattern features objectively demonstrate the substantial impact these features have on model performance.

Analysis of churn predictions with respect to financial literacy provides an insight into the complexities associated with customer relationship management.

To my knowledge this is the first study to comprehensively detail the implementation of a customer churn prediction framework for a leading Australian superannuation fund. Future work will focus on evaluating the effectiveness of super guarantee churn in delivering timely and relevant predictions in contrast to account churn prediction.

6. Conclusion

Financial literacy in superannuation is vitally important for all Australian's. Through a combination of product innovation and government reform over ninety percent of the workforce who hold retirement savings in a superannuation fund are facing increasingly complex decisions and risks in navigating their journey to retirement. Numerous studies have demonstrated the positive outcomes associated with high financial sophistication. Studies have shown that financially literate individuals are more likely to participate and earn more in risky markets, they are more likely to seek qualified sources of financial advice, and they are better at financial planning and debt management. Despite the well understood benefits of financial literacy, levels across Australia remain low. Many Australian's are able to correctly answer basic financial knowledge questions, nor can they articulate how their superannuation investments work. As a consequence, there is a funding gap in Australian superannuation. In 2014, the funding gap was estimated to be $768bn, or $70,100 per person including provisions for the aged pension. Due to recent events globally, many Australian's have been forced to dip in to their retirement savings through special purpose COVID-19 withdrawals of up to $20,000. Those who have been compelled to withdraw from their super are likely to fall further behind in their retirement savings journey, and the retirement savings gap is expected to grow. It is acknowledged that the current 9.5% super guarantee rate is insufficient to provide lifetime retirement savings. Though this rate is expected to change in the near future, the positive outcomes associated with this will not be seen for another generation. Furthermore, the government have tightened the eligibility requirements for the aged pension in recent years, and this is expected to continue in response to the growing retired population. Therefore, with 5.5 million Australians expected to retire between 2011 and 2030 and a diminishing government safety net more Australians will be living in poverty in retirement. For a superannuation fund, ensuring that its members have the requisite skills and knowledge to safely navigate their journey to retirement is critically important.

6.1. Contributions

The contributions of this research are best described as being theoretical or practical. The theoretical contributions include the development of a new construct for the measurement of financial literacy in superannuation, and its prediction. The practical contributions of this research are best described by the findings in chapter 6, whereby the superannuation literacy framework is tested against real world data.

The development of a framework for the ongoing measurement of financial literacy in superannuation is of vital importance to superannuation trustees concerned with the retirement well-being of its members. This research set out to develop a passive outcomes based measurement and prediction framework for financial literacy in superannuation. To achieve this, this research has utilised the results of a financial literacy survey issued to superannuation members to design a construct for superannuation literacy. This construct has been validated against positive outcomes and financial habits, and demonstrated to outperform the benchmark financial literacy measure.

Using this construct, I then develop a prediction framework for superannuation literacy using machine learning algorithms for regression. The prediction framework is built and validated on the largest administrative dataset ever made available for financial literacy research. To maximise the predictive performance of the model, while addressing non-response bias I propose and validate a novel prediction framework titled; debiased multi-output regression (DMR). The proposed framework is shown to outperform seven other leading algorithms for machine learning and regression, and is tuned to maximise the correlation coefficient of aggregate predictions and a list of financial outcomes.

Finally, this research has validated the results of the prediction framework against a key metric for member performance, account attrition. The results show that there is a strong positive correlation between the two metrics, providing significant insight into the management of customers and design of products for them.

6.2. Applications

The potential applications for this research are vast. As an industry endorsed research initiative, the measurement and prediction framework will used to guide a number of customer interactions and interventions for the industry partner, Colonial First State.

First, measurements of financial literacy will be used to complement an existing program of work aimed at identifying and supporting vulnerable members. Members with low financial literacy often belong to the lowest income and education cohorts of society and are at the greatest risk of making mistakes in the management of their superannuation savings. As articulated in the findings of the Banking Royal Commission vulnerable members are not just those who fit the model of what may be typically perceive to represent vulnerability rather anyone who is at risk of detriment due to a knowledge gap or personal circumstances should be regarded as vulnerable. Through this initiative the lowest decile of financial literacy scores will be prioritised for financial health checks, guided superannuation on-boarding and will be offered low-cost options to connect with qualified financial advice.

Furthermore, the framework will support targeted marketing and education programs. Through this research it has been discussed how complex education programs can damage the confidence of individuals and cause them to shirk positive engagement with their finances. Using superannuation literacy scores, news and educational content can be directed to those members best suited to it. Feedback mechanisms will be implemented through the public website and for electronic direct mailing to ascertain the relevance of the content to the targeted cohort. Through this mechanism additional models will be built to align content to superannuation literacy cohorts.

In the future, additional applications in Colonial First State will include; customer protection and advocacy, product and service innovation, retirement planning and tailored financial advice, and risk monitoring. In chapter 6 it was demonstrated that superannuation literacy represents an opportunity for transfer learning between domains – superannuation literacy is not only predictive of financial outcomes, but also member behaviour. Superannuation literacy scores will then also be used to compliment vast array of data driven decisions within the organisation.

6.3. Future work

This thesis concludes with three recommendations for future studies.

First, additional research should be explore a wider variety of positive financial and non-financial outcomes for the validation of the measurement construct. These additional outcome metrics, along with those introduced through this research should be evaluated against long-term outcomes.

In addition, through industry applications, studies should explore the efficacy of efforts to lift the financial literacy of individuals. Research suggests that there is a delicate balance between objective and subjective knowledge and that interventions targeting only objective knowledge can be detrimental to individuals.

Finally, prescriptive analysis should be conducted on this framework to provide insights into the leverage points for financial literacy. An understanding of the variables which greatly influence financial literacy in superannuation will assist in defining meaningful interventions.

Bibliography

Abd Elrahman, S.M. and Abraham, A., 2013. A review of class imbalance problem. Journal of Network and Innovative Computing, 1(2013), pp.332-340.

Agarwal, S., Skiba, P.M. & Tobacman, J. 2009, 'Payday loans and credit cards: New liquidity and credit scoring puzzles?', *American Economic Review*, vol. 99, no. 2, pp. 412-17.

Ali, Ö.G. & Arıtürk, U. 2014, 'Dynamic churn prediction framework with more effective use of rare event data: The case of private banking', Expert Systems with Applications, vol. 41, no. 17, pp. 7889-903.

Appice, A. & Džeroski, S. 2007, 'Stepwise induction of multi-target model trees', European conference on machine learning, Springer, pp. 502-9.

Agnew, J.R., Bateman, H. & Thorp, S. 2013, 'Financial literacy and retirement planning in Australia', *Numeracy: Advancing Education in Quantitative Literacy*, vol. 6, no. 2.

APRA 2016, '*Annual Superannuation Bulletin',* Australian Prudential Regulation Authority, Canberra, viewed 2 October 2017, <http://www.apra.gov.au/Super/Documents/2016ASBPDF201506.pdf>.

Bateman, H., Eckert, C., Geweke, J., Louviere, J., Thorp, S. & Satchell, S. 2012, 'Financial competence and expectations formation: Evidence from Australia', *Economic Record*, vol. 88, no. 280, pp. 39-63.

Ballings, M. & Van den Poel, D. 2012, 'Customer event history for churn prediction: How long is long enough?', *Expert Systems with Applications*, vol. 39, no. 18, pp. 13517-22.

Bateman, H., Deetlefs, J., Dobrescu, L.I., Newell, B.R., Ortmann, A. & Thorp, S. 2014, 'Just interested or getting involved? An analysis of superannuation attitudes and actions', *Economic Record*, vol. 90, no. 289, pp. 160-78.

Bateman, H., Eckert, C., Geweke, J., Louviere, J.J., Satchell, S.E. & Thorp, S. 2011, 'Financial competence, risk presentation and retirement portfolio preferences', UNSW Australian School of Business Research Paper, no. 2011ACTL03.

Bateman, H., Eckert, C., Geweke, J., Louviere, J., Thorp, S. & Satchell, S. 2012, 'Financial competence and expectations formation: Evidence from Australia', *Economic Record*, vol. 88, no. 280, pp. 39-63.

Blume, M., Lazarus, M.A., Peranich, L.S., Vernhes, F., Caid, W.R., Dunning, T.E., Russell, G.R. & Sitze, K.L. 2005, 'Predictive modeling of consumer financial behavior using supervised segmentation and nearest-neighbor matching', Google Patents.

Borchani, H., Varando, G., Bielza, C. and Larranaga, P., 2015. A survey on multi-output regression. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, *5*(5), pp.216-233.

Breiman, L. 2001, 'Random forests', Machine learning, vol. 45, no. 1, pp. 5-32.

Broadway, B., de New, J. 2014, ‘The importance of economic expectations for retirement entry’, The University of Melbourne: Melbourne Institute of Applied Economic and Social Research, Melbourne, viewed 21 August 2020, viewed 21 August 2020, <https://melbourneinstitute.unimelb.edu.au/downloads/working_paper_series/wp2014n28.pdf>

Buettner, R. 2017, 'Predicting user behavior in electronic markets based on personality-mining in large online social networks', *Electronic Markets*, vol. 27, no. 3, pp. 247-65.

Burez, J. & Van den Poel, D. 2009, 'Handling class imbalance in customer churn prediction', *Expert Systems with Applications*, vol. 36, no. 3, pp. 4626-36.

Burnett, J., Davis, K.T., Murawski, C., Wilkins, R. & Wilkinson, N. 2014, 'Measuring adequacy of retirement savings', The University of Melbourne: Melbourne Institute of Applied Economic and Social Research, Melbourne, viewed 21 August 2020, <https://www.melbourneinstitute.com/downloads/working_paper_series/wp2014n05.pdf>.

Calvet, L.E., Campbell, J.Y. & Sodini, P. 2007, 'Down or out: Assessing the welfare costs of household investment mistakes', *Journal of Political Economy*, vol. 115, no. 5, pp. 707-47.

Calvet, L.E., Campbell, J.Y. & Sodini, P. 2009, 'Measuring the financial sophistication of households', *American Economic Review*, vol. 99, no. 2, pp. 393-98.

Campbell, J.Y. 2006, 'Household finance', *The journal of finance*, vol. 61, no. 4, pp. 1553-604.

Chawla, N.V., Bowyer, K.W., Hall, L.O. and Kegelmeyer, W.P., 2002. SMOTE: synthetic minority over-sampling technique. Journal of artificial intelligence research, 16, pp.321-357.

Chen, T. & Guestrin, C. 2016, 'Xgboost: A scalable tree boosting system', Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining, pp. 785-94.

Chu, C., Xu, G., Brownlow, J. & Fu, B. 2016, 'Deployment of churn prediction model in financial services industry', 2016 International Conference on Behavioral, Economic and Socio-cultural Computing (BESC), IEEE, pp. 1-2.

Chu, Z., Wang, Z., Xiao, J.J. & Zhang, W. 2017, 'Financial literacy, portfolio choice and financial well-being', *Social Indicators Research*, vol. 132, no. 2, pp. 799-820.

Clark, R., Lusardi, A. & Mitchell, O.S. 2017, 'Financial knowledge and 401 (k) investment performance: a case study', *Journal of Pension Economics & Finance*, vol. 16, no. 3, pp. 324-47.

Clark, R.L., Hammond, R.G. & Vanderweide, D. 2019, 'Navigating complex financial decisions at retirement: evidence from annuity choices in public sector pensions', *Journal of Pension Economics & Finance*, vol. 18, no. 4, pp. 594-611.

Collobert, R. & Weston, J. 2008, 'A unified architecture for natural language processing: Deep neural networks with multitask learning', Proceedings of the 25th international conference on Machine learning, pp. 160-7.

Coussement, K. & De Bock, K.W. 2013, 'Customer churn prediction in the online gambling industry: The beneficial effect of ensemble learning', *Journal of Business Research*, vol. 66, no. 9, pp. 1629-36.

Coussement, K. & Van den Poel, D. 2008, 'Churn prediction in subscription services: An application of support vector machines while comparing two parameter-selection techniques', *Expert systems with applications*, vol. 34, no. 1, pp. 313-27.

de Bassa Scheresberg, C. 2013, 'Financial literacy and financial behavior among young adults: Evidence and implications', *Numeracy*, vol. 6, no. 2, p. 5.

Delpachitra, S. & Rafizadeh, S. 2014, 'The switching decision: Are members of superannuation funds rational and informed investors?', *Australasian Accounting Business & Finance Journal*, vol. 8, no. 4, pp. 45-62.

Dietrich, T., Rundle-Thiele, S. & Kubacki, K. 2017, Segmentation in social marketing, Springer.

Drexler, A., Fischer, G. and Schoar, A., 2014. Keeping it simple: Financial literacy and rules of thumb. *American Economic Journal: Applied Economics*, 6(2), pp.1-31.

Džeroski, S., Demšar, D. & Grbović, J. 2000, 'Predicting chemical parameters of river water quality from bioindicator data', *Applied Intelligence*, vol. 13, no. 1, pp. 7-17.

Gaillard, P. and Gerchinovitz, S., 2015, June. A chaining algorithm for online nonparametric regression. In *Conference on Learning Theory* (pp. 764-796). PMLR.

Gallery, N., Newton, C. & Palm, C. 2011, 'Framework for assessing financial literacy and superannuation investment choice decisions', *Australasian Accounting Business & Finance Journal*, vol. 5, no. 2, p. 3.

Gerrans, P., Clark-Murphy, M. & Truscott, K. 2009, 'Financial literacy and superannuation awareness of indigenous Australians: Pilot study results', *Australian Journal of Social Issues*, vol. 44, no. 4, pp. 417-39.

Gruen, D. and Soding, L., 2011. Compulsory superannuation and national saving. *Economic Round-up*, (3), pp.45-56.

Guiso, L. & Jappelli, T. 2008, 'The role of intuition and reasoning in driving aversion to risk, aversion to ambiguity and regret', Mimeo.

Hadar, L., Sood, S. & Fox, C.R. 2013, 'Subjective knowledge in consumer financial decisions', *Journal of Marketing Research*, vol. 50, no. 3, pp. 303-16.

Hastings, J.S., Madrian, B.C. & Skimmyhorn, W.L. 2013, 'Financial literacy, financial education, and economic outcomes', *Annu. Rev. Econ.*, vol. 5, no. 1, pp. 347-73.

He, H. and Garcia, E.A., 2009. Learning from imbalanced data. *IEEE Transactions on knowledge and data engineering*, 21(9), pp.1263-1284.

Hill, R.R. & Perdue, G. 2008, 'A methodological issue in the measurement of financial literacy', *Journal of Economics & Economic Education Research*, vol. 9, no. 2, pp. 43 - 59.

Hogarth, J.M., Anguelov, C.E. & Lee, J. 2005, 'Who has a bank account? Exploring changes over time, 1989–2001', *Journal of Family and Economic Issues*, vol. 26, no. 1, pp. 7-30.

Huang, R., Samy, M., Tawfik, H. & Nagar, A. 2008, 'Application of Support Vector Machines in Financial Literacy Modelling', Computer Modeling and Simulation, 2008. EMS'08. Second UKSIM European Symposium on, IEEE, pp. 311-6.

Huang, R., Tawfik, H., Samy, M. & Nagar, A. 2007, 'A Financial Literacy Simulation Model using Neural Networks: Case Study', Innovations in Information Technology, 2007. IIT'07. 4th International Conference on, IEEE, pp. 516-20.

Huang, Y., Zhu, F., Yuan, M., Deng, K., Li, Y., Ni, B., Dai, W., Yang, Q. & Zeng, J. 2015, 'Telco churn prediction with big data', Proceedings of the 2015 ACM SIGMOD international conference on management of data, pp. 607-18.

Hugo, G. & SA, A. 2014, 'The demographic facts of ageing in Australia', Appendix Q for Aged Care Financing Authority Second Annual Report 2014.

Hung, A.A., Parker, A.M. and Yoong, J., 2009. Defining and measuring financial literacy (RAND Working Paper WR-708). Social Science Research Network. Retrieved September, 8, p.2016.

Huston, S.J. 2010, 'Measuring financial literacy', *Journal of Consumer Affairs*, vol. 44, no. 2, pp. 296-316.

Ibrahim, M.E. & Alqaydi, F.R. 2013, 'Financial literacy, personal financial attitude, and forms of personal debt among residents of the UAE', *International Journal of Economics and Finance*, vol. 5, no. 7, p. 126.

Idris, A., Rizwan, M. & Khan, A. 2012, 'Churn prediction in telecom using Random Forest and PSO based data balancing in combination with various feature selection strategies', *Computers & Electrical Engineering*, vol. 38, no. 6, pp. 1808-19.

Jappelli, T. & Padula, M. 2013, 'Investment in financial literacy and saving decisions', *Journal of Banking & Finance*, vol. 37, no. 8, pp. 2779-92.

Jappelli, T. & Padula, M. 2015, 'Investment in financial literacy, social security, and portfolio choice', *Journal of Pension Economics & Finance*, vol. 14, no. 4, pp. 369-411.

Joly, A., Wehenkel, L. and Geurts, P., 2019. Gradient tree boosting with random output projections for multi-label classification and multi-output regression. *arXiv preprint arXiv:1905.07558*.

Kasozi, J. and Makina, D., 2021. Analysis of financial literacy and its effects on financial inclusion in Uganda. *International Journal of Finance & Banking Studies (2147-4486)*, *10*(3), pp.67-83.

Kimball, M.S. & Shumway, T. 2010, 'Investor sophistication and the home bias, diversification, and employer stock puzzles', *Diversification, and Employer Stock Puzzles (January 29, 2010)*.

Kocev, D., Vens, C., Struyf, J. & Džeroski, S. 2013, 'Tree ensembles for predicting structured outputs', *Pattern Recognition*, vol. 46, no. 3, pp. 817-33.

Lazarus, M.A., Blume, A.M., Brown, K.B., Caid, W.R., Dunning, T.E., Peranich, L.S., Russell, G.R. & Sitze, K.L. 2002, 'Predictive modeling of consumer financial behavior', Google Patents.

Li, H., Zhang, W., Chen, Y., Guo, Y., Li, G.-Z. & Zhu, X. 2017, 'A novel multi-target regression framework for time-series prediction of drug efficacy', *Scientific reports*, vol. 7, no. 1, pp. 1-9.

Li, X. 2020, 'When financial literacy meets textual analysis: A conceptual review', *Journal of Behavioral and Experimental Finance*, p. 100402.

Liu, H., Cai, J. and Ong, Y.S., 2018. Remarks on multi-output Gaussian process regression. *Knowledge-Based Systems*, *144*, pp.102-121.

Liu, L. and Zhang, H., 2021. Financial literacy, self-efficacy and risky credit behavior among college students: Evidence from online consumer credit. Journal of Behavioral and Experimental Finance, p.100569.

Lusardi, A. & Mitchell, O.S. 2007, 'Baby boomer retirement security: The roles of planning, financial literacy, and housing wealth', *Journal of Monetary Economics*, vol. 54, no. 1, pp. 205-24.

Lusardi, A. & Mitchell, O.S. 2008, 'Planning and financial literacy: How do women fare?', *American Economic Review*, vol. 98, no. 2, pp. 413-17.

Lusardi, A. & Mitchell, O.S. 2011a, *Financial literacy and planning: Implications for retirement wellbeing*, National Bureau of Economic Research.

Lusardi, A. & Mitchell, O.S. 2011b, 'Financial literacy around the world: an overview', *Journal of pension economics & finance*, vol. 10, no. 4, pp. 497-508.

Lusardi, A. & Mitchell, O.S. 2014, 'The economic importance of financial literacy: Theory and evidence', *Journal of Economic Literature*, vol. 52, no. 1, pp. 5-44.

Lusardi, A. & Mitchell, O.S. 2017, 'How ordinary consumers make complex economic decisions: Financial literacy and retirement readiness', *Quarterly Journal of Finance*, vol. 7, no. 03, p. 1750008.

Lusardi, A. & Mitchelli, O.S. 2007, 'Financial literacy and retirement preparedness: Evidence and implications for financial education', *Business economics*, vol. 42, no. 1, pp. 35-44.

Lusardi, A. & Tufano, P. 2009, *Debt literacy, financial experiences, and overindebtedness*, National Bureau of Economic Research.

Mandell, L. & Klein, L.S. 2007, 'Motivation and financial literacy', *Financial services review*, vol. 16, no. 2.

Mastelini, S.M., da Costa, V.G.T., Santana, E.J., Nakano, F.K., Guido, R.C., Cerri, R. and Barbon, S., 2019. Multi-output tree chaining: An interpretative modelling and lightweight multi-target approach. *Journal of Signal Processing Systems*, *91*(2), pp.191-215.

McDaniel, L., Martin, R.D. and Maines, L.A. 2002. Evaluating financial reporting quality: The effects of financial expertise vs. financial literacy. *The accounting review*, 77(s-1), pp.139-167.

Melki, G., Cano, A., Kecman, V. and Ventura, S., 2017. Multi-target support vector regression via correlation regressor chains. *Information Sciences*, *415*, pp.53-69.

Mooney, C.H. & Roddick, J.F. 2013, 'Sequential pattern mining--approaches and algorithms', ACM Computing Surveys (CSUR), vol. 45, no. 2, pp. 1-39.

OECD 2014, *PISA 2012 Results: Students and Money (Volume VI)*: *Financial literacy skills for the twenty-first century*

Organisation for Economic Co-Operation and Development. 2013, 'Financial literacy and inclusion: Results of OECD/INFE survey across countries and by gender, OECD Centre, Paris, France

Phua, C., Cao, H., Gomes, J.B. & Nguyen, M.N. 2012, 'Predicting near-future churners and win-backs in the telecommunications industry', arXiv preprint arXiv:1210.6891.

Popović, D. & Bašić, B.D. 2009, 'Churn prediction model in retail banking using fuzzy C-means algorithm', Informatica, vol. 33, no. 2.

Potrich, A.C.G., Vieira, K.M. & Kirch, G. 2015, 'Determinants of financial literacy: Analysis of the influence of socioeconomic and demographic variables', Revista Contabilidade & Finanças, vol. 26, no. 69, pp. 362-77.

Purver, M., Körding, K.P., Griffiths, T.L. & Tenenbaum, J.B. 2006, 'Unsupervised topic modelling for multi-party spoken discourse', Proceedings of the 21st International Conference on Computational Linguistics and 44th Annual Meeting of the Association for Computational Linguistics, pp. 17-24.

Rice Warner 2014*, 'Retirement savings gap at 30 June 2014'*, Rice Warner Pty Ltd, viewed 16 May 2019, https://www.ricewarner.com/wp-content/uploads/2015/12/Retirement-Savings-Gap-as-at-30-June-2014.pdf

Rowe, M. 2013, 'Mining user lifecycles from online community platforms and their application to churn prediction', *2013 IEEE 13th International Conference on Data Mining*, IEEE, pp. 637-46.

Runge, J., Gao, P., Garcin, F. & Faltings, B. 2014, 'Churn prediction for high-value players in casual social games', *2014 IEEE conference on Computational Intelligence and Games*, IEEE, pp. 1-8.

Samy, M., Tawfik, H., Huang, R. and Nagar, A.K., 2008. Financial literacy of youth-a sensitivity analysis of the determinants. *International Journal of Economic Sciences and Applied Research*, 1(1).

Santini, F.D.O., Ladeira, W.J., Mette, F.M.B. & Ponchio, M.C. 2019, 'The antecedents and consequences of financial literacy: a meta-analysis', *International Journal of Bank Marketing.*

Servon, L.J. & Kaestner, R. 2008, 'Consumer financial literacy and the impact of online banking on the financial behavior of lower-income bank customers', *Journal of Consumer Affairs*, vol. 42, no. 2, pp. 271-305.

Shi, Z., Hospedales, T.M. & Xiang, T. 2013, 'Bayesian joint topic modelling for weakly supervised object localisation', Proceedings of the IEEE International Conference on Computer Vision, pp. 2984-91.

Sood, M. and Bhushan, P., 2017. Efficacy of artificial neural network for financial literacy prediction. *International Journal of Advanced Research in IT and Engineering*, 6(2), pp.1-8.

Stolper, O.A. & Walter, A. 2017, 'Financial literacy, financial advice, and financial behavior', *Journal of business economics*, vol. 87, no. 5, pp. 581-643.

Sucar, L. E., Bielza, C., Morales, E. F., Hernandez-Leal, P., Zaragoza, J. H. & Larra~naga, P., 2014, `Multi-label classication with bayesian network based chain classiers', *Pattern Recognition Letters*, vol. 41, pp. 14-22.

Sun, Y., Kamel, M. S., Wong, A. K. & Wang, Y., 2007, `Cost-sensitive boosting for classication of imbalanced data', *Pattern Recognition*, vol. 40, no. 12, pp. 3358-3378.

Sun, Y., Xue, B., Zhang, M. et al., 2019, `Evolving deep convolutional neural networks for image classication', *IEEE Transactions on Evolutionary Computation*, vol. 24, no. 2, pp. 394-407.

Tibshirani, R., Saunders, M., Rosset, S., Zhu, J. & Knight, K. 2005, 'Sparsity and smoothness via the fused lasso', *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, vol. 67, no. 1, pp. 91-108.

Tikhonov, A.N. & Arsenin, V.Y. 1977, 'Solutions of ill-posed problems', New York, vol. 1, p. 30.

Tsai, C.-F. & Chen, M.-Y. 2010, 'Variable selection by association rules for customer churn prediction of multimedia on demand', *Expert Systems with Applications*, vol. 37, no. 3, pp. 2006-15.

Tsoumakas, G., Katakis, I. and Vlahavas, I., 2009. Mining multi-label data. In *Data mining and knowledge discovery handbook* (pp. 667-685). Springer, Boston, MA.

Tsoumakas, G., Katakis, I. & Vlahavas, I., 2011, `Random k-labelsets for multilabel classifcation', *IEEE Transactions on Knowledge and Data Engineering*, vol. 23, no. 7, pp. 1079-1089.

Van Rooij, M., Lusardi, A. & Alessie, R. 2011, 'Financial literacy and stock market participation', *Journal of Financial Economics*, vol. 101, no. 2, pp. 449-72.

Van Rooij, M.C., Lusardi, A. & Alessie, R.J. 2011, 'Financial literacy and retirement planning in the Netherlands', *Journal of Economic Psychology*, vol. 32, no. 4, pp. 593-608.

Vo, N.N., Liu, S., Li, X. & Xu, G. 2021, 'Leveraging unstructured call log data for customer churn prediction', *Knowledge-Based Systems*, vol. 212, p. 106586.

Warner, R. 2014, Retirement savings gap at 30 June 2014, Rice Warner Pty Ltd.

Wang, B. & Pineau, J. 2015, 'Online boosting algorithms for anytime transfer and multitask learning', *Twenty-Ninth AAAI Conference on Artificial Intelligence*.

Wang, P., Sun, W., Yin, D., Yang, J. & Chang, Y. 2015, 'Robust tree-based causal inference for complex ad effectiveness analysis', *Proceedings of the Eighth ACM International Conference on Web Search and Data Mining*, ACM, pp. 67-76.

Wang, S., Liu, W., Wu, J., Cao, L., Meng, Q. and Kennedy, P.J., 2016, July. Training deep neural networks on imbalanced data sets. In *2016 international joint conference on neural networks (IJCNN)* (pp. 4368-4374). IEEE.

Worthington, A.C. 2006, 'Predicting financial literacy in Australia', *Financial Services Review,* vol. 15, no. 1, p. 59.

Wright, A.P., Wright, A.T., McCoy, A.B. & Sittig, D.F. 2015, 'The use of sequential pattern mining to predict next prescribed medications', *Journal of biomedical informatics*, vol. 53, pp. 73-80.

Wu, X., Kumar, V., Quinlan, J. R., Ghosh, J., Yang, Q., Motoda, H., McLachlan, G. J., Ng, A., Liu, B., Philip, S. Y. et al., 2008, `Top 10 algorithms in data mining', *Knowledge and information systems*, vol. 14, no. 1, pp. 1-37.

Xiao, Y. & Ye, W., 2010, `Survey of feature normalization techniques for robust speech recognition', *Journal of Chinese information processing*, vol. 24, no. 05, pp. 106-116.

Xie, Y., Li, X., Ngai, E. & Ying, W. 2009, 'Customer churn prediction using improved balanced random forests', *Expert Systems with Applications*, vol. 36, no. 3, pp. 5445-9.

Xu, S., An, X., Qiao, X., Zhu, L. and Li, L., 2013. Multi-output least-squares support vector regression machines. *Pattern Recognition Letters*, *34*(9), pp.1078-1084.

Zhang, M.-L. & Zhou, Z.-H. 2007, 'ML-KNN: A lazy learning approach to multi-label learning', *Pattern recognition*, vol. 40, no. 7, pp. 2038-48.

Zheng, Z., Wei, W., Liu, C., Cao, W., Cao, L. & Bhatia, M. 2016, 'An effective contrast sequential pattern mining approach to taxpayer behavior analysis', *World Wide Web*, vol. 19, no. 4, pp. 633-51.

Zou, H. & Hastie, T. 2005, 'Regularization and variable selection via the elastic net', *Journal of the royal statistical society: series B (statistical methodology)*, vol. 67, no. 2, pp. 301-20.