FACTORS WITH RETIREMENT BEHAVIOUR AMONG RETIREES AND PRE-RETIREES IDENTIFIED WITH A MACHINE LEARNING METHOD

MUHAMMAD AIZAT BIN ZAINAL ALAM

FACULTY OF BUSINESS AND ECONOMICS
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KUALA LUMPUR

2023

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MUHAMMAD AIZAT BIN ZAINAL ALAM

THESIS SUBMITTED IN FULFILMENT OF THE REQUIREMENTS FOR THE DEGREE OF DOCTOR OF PHILOSOPHY

FACULTY OF BUSINESS AND ECONOMICS
UNIVERSITI MALAYA
KUALA LUMPUR

2023

UNIVERSITI MALAYA

ORIGINAL LITERARY WORK DECLARATION

Name of Candidate: **MUHAMMAD AIZAT BIN ZAINAL ALAM**

Matric No: **17050423/2**

Name of Degree: **DOCTOR OF PHILOSOPHY**

Title Thesis: **FACTORS WITH RETIREMENT BEHAVIOUR AMONG RETIREES AND PRE-RETIREES IDENTIFIED WITH A MACHINE LEARNING METHOD**

Field of Study: **Social and Behavioural Science**

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FACTORS WITH RETIREMENT BEHAVIOUR AMONG RETIREES AND PRE-RETIREES IDENTIFIED WITH A MACHINE LEARNING METHOD

ABSTRACT

The Malaysian population is greying, and most individuals were found not prepared for it. Many are implied to have low retirement savings as retirement was found considered not a top priority by Malaysians. With studies on the psychology of retirement driven by the rise of behavioural economics, the mental accounting effect where the prospect of gains and losses are weighted differently, and violation of fungibility between different categories of wealth and expenditure as per classical economic theory which impacts retirement behaviour can be anchored upon to explore further ways towards retirement preparedness among Malaysians given limited yet growing number of studies conducted to understand retirement among Malaysians. The Malaysian Ageing and Retirement Survey (MARS) Data Wave 1 is used for this study where the data was sampled via multiple-stage sampling framework where each region is stratified by urban and rural areas called enumeration blocks (EBs) which are proportionate to the population size of each region across 3,384 households. This study uses 3,067 responses which are then be coupled with a machine learning methodology (ranging from Naïve Bayesian, Generalised Linear Model, Logistic Regression, Artificial Neural Network, Decision Tree, Random Forest, and Gradient Boosted Trees) via RapidMiner Studio to expand the understanding of how categories of wealth and expenditures can affect retirement behaviour, given the increasingly important role of machine learning algorithms within the context of behavioural economics where it has been demonstrated to describe patterns and relationships in behavioural data better than standard statistical analysis. In this regard, it was found that a vast majority of individuals exhibit mental accounting behaviour (66% of total respondents weight the prospect of gains and losses differently), where it was also found that future income wealth category, such as retirement savings, have most predictive weightage on retirement satisfaction based on an artificial neural network model (ANN) with an accuracy rate of 80.33%. Moreover, a re-ranking of wealth priorities for pre-retirees who often think about retirement is called for to ensure that they achieve satisfaction later in retirement. Towards being more prepared for retirement, pre-retirees are encouraged to move from heavily saving in current assets wealth category such as in fixed deposits (which has the highest predictive weightage on the tendency of thinking about retirement based on an ANN model with an accuracy rate of 65.80%) towards more savings in future income wealth category such as in Private Retirement Schemes (PRS). It is demonstrated that not only mental accounting behaviour, but also the allocation according to mental accounting categories on top of demographic variables may have impact on retirement behaviour. Importantly, the evaluation of retirement wellbeing should equally focus on financial and psychological perspectives to ensure both are optimised accordingly, where organisations should focus on avenues to enhance an individual's future income wealth category to enhance savings adequacy and retirement preparedness while the government can consider ways to improve income to encourage higher savings rate in tandem with the increasing provision of financial and psychological education on managing personal finances to the Malaysian population.

Keywords: behavioural finance, human decision-making, machine learning, mental accounting, retirement planning

FAKTOR-FAKTOR TINGKAH LAKU PERSARAAN DALAM KALANGAN PESARA DAN PRA-PESARA DIKENAL PASTI DENGAN KAEDAH PEMBELAJARAN MESIN

ABSTRAK

Penduduk Malaysia semakin menua, dan kebanyakan individu didapati tidak bersedia untuk menghadapinya. Ramai yang difahami mempunyai simpanan persaraan yang rendah kerana persaraan didapati tidak menjadi keutamaan rakyat Malaysia. Dengan kajian psikologi persaraan yang didorong oleh peningkatan ekonomi tingkah laku, kesan perakaunan mental di mana prospek keuntungan dan kerugian ditimbang secara berbeza, dan pelanggaran ketergantungan antara kategori kekayaan dan perbelanjaan yang berbeza mengikut teori ekonomi klasik yang memberi kesan kepada tingkah laku persaraan boleh digunakan untuk meneroka cara lebih lanjut ke arah kesediaan persaraan dalam kalangan rakyat Malaysia memandangkan bilangan kajian yang dijalankan untuk memahami persaraan dalam kalangan rakyat Malaysia yang terhad namun semakin meningkat. Tinjauan Penuaan dan Persaraan Malaysia (MARS) Data Gelombang 1 digunakan untuk kajian ini di mana data sampel telah diambil melalui rangka kerja persampelan berbilang peringkat di mana setiap wilayah berstrata mengikut kawasan bandar dan luar bandar yang dipanggil blok enumerasi (EB) yang berkadar dengan populasi saiz setiap wilayah merentasi 3,384 isi rumah. Kajian ini menggunakan 3,067 respons yang kemudiannya digabungkan dengan metodologi pembelajaran mesin (bermula daripada Naïve Bayesian, Model Linear Umum, Regresi Logistik, Rangkaian Neural Buatan, Pokok Keputusan, Hutan Rawak dan Pokok Didorong Kecerunan) melalui RapidMiner Studio untuk meluaskan pemahaman bagaimana kategori kekayaan dan perbelanjaan boleh mempengaruhi tingkah laku persaraan, memandangkan peranan algoritma pembelajaran mesin yang semakin penting dalam konteks ekonomi tingkah laku di mana ia telah ditunjukkan untuk menerangkan corak dan hubungan dalam data tingkah laku lebih baik daripada analisis statistik standard. Dalam hal ini, didapati bahawa sebahagian besar individu menunjukkan tingkah laku perakaunan mental (66% daripada jumlah responden menimbang prospek keuntungan dan kerugian secara berbeza), di mana ia juga didapati bahawa kategori kekayaan pendapatan masa hadapan, seperti simpanan persaraan, mempunyai paling banyak ramalan wajaran pada kepuasan persaraan berdasarkan model rangkaian saraf tiruan (ANN) dengan kadar ketepatan 80.33%. Lebih-lebih lagi, penarafan semula keutamaan kekayaan untuk pra-pesara yang sering memikirkan tentang persaraan diperlukan untuk memastikan mereka mencapai kepuasan selepas bersara. Ke arah lebih bersedia untuk bersara, pra-pesara digalakkan untuk beralih daripada menyimpan banyak dalam kategori kekayaan aset semasa seperti dalam simpanan tetap (yang mempunyai wajaran ramalan tertinggi mengenai kecenderungan berfikir tentang persaraan berdasarkan model ANN dengan kadar ketepatan sebanyak 65.80%) ke arah lebih banyak simpanan dalam kategori kekayaan pendapatan masa hadapan seperti dalam Skim Persaraan Swasta (PRS). Ia ditunjukkan bahawa bukan sahaja tingkah laku perakaunan mental, tetapi juga peruntukan mengikut kategori perakaunan mental di atas pembolehubah demografi mungkin mempunyai kesan ke atas tingkah laku persaraan. Yang penting, penilaian kesejahteraan persaraan harus sama-sama menumpukan pada perspektif kewangan dan psikologi untuk memastikan kedua-duanya dioptimumkan dengan sewajarnya, di mana organisasi harus menumpukan pada jalan untuk meningkatkan kategori kekayaan pendapatan masa depan individu untuk meningkatkan kecukupan simpanan dan kesediaan persaraan sementara kerajaan boleh mempertimbangkan cara untuk meningkatkan pendapatan untuk menggalakkan kadar simpanan yang lebih tinggi seiring dengan peningkatan penyediaan pendidikan kewangan dan psikologi untuk menguruskan kewangan peribadi kepada penduduk Malaysia.

Kata kunci: tingkah laku kewangan, daya membuat keputusan manusia, pembelajaran mesin, perakaunan mental, perancangan persaraan

ACKNOWLEDGEMENTS

I would like to express my deepest gratitude to God, for without His mercy, none of these may ever happen.

My gratitude also goes to my supervisors, Associate Professor Dr Yong Chen Chen and Professor Datuk Dr Norma Mansor, for without their guidance, I may not have been able to complete my thesis.

To my parents, my wife Aliah Amil, and siblings, thank you for your understanding and help in making this study a reality. To my late grandmother, Mdm Wan Teh Ismail and my son Asif Yusof Khan, your love will always be my pillar of strength.

To my best friends from my bachelor's degree years, Qila, Fitri, and Jida, your help and moral support means a lot to me.

Lastly, to University of Malaya and the Government of Malaysia through the Ministry of Higher Education for their support for fellow citizens in advancing themselves through education.

Thank you.

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i.	%	:	Percentage
ii.	e.g.	:	for example
iii.	i.e.	:	in other words

CHAPTER 1 : INTRODUCTION

1.1 Introduction

Over the years after independence, Malaysians have seen their quality of life improve with the lowering of the poverty rate and increase in household income. Like many countries, Malaysia is experiencing an ageing population, and the trend is expected to accelerate towards an aged and super-aged nation in the future (Hamid et al., 2021; Securities Commission Malaysia, 2021). Despite these developments, there is a heightened concern and plenty of evidence for inadequate retirement savings brought by a lack of good savings behaviour and lowered retirement wellbeing among Malaysians (Employees Provident Fund [EPF], 2021). This fact points towards low levels of retirement preparedness, despite interventions introduced to mitigate this issue as evidenced in previous literature and public official documents. Clearly, having good financial knowledge and financial literacy does not necessarily guarantee an individual is prepared for retirement, given that homo sapiens differ from homo economicus in which the assumption of rationality in humans should be abandoned. This fact inherently renders a critical assessment of retirement with a special focus on behavioural economics considerations, where targeted policies may be crafted for individuals of differing retirement preparedness levels. Retirement preparedness relates to having adequate resources for retirement. On an individual basis, a person is theorised to exhibit mental accounting behaviour where income and/or expenses are organised, evaluated, recorded, and allocated into a set of categories as a shortcut to handle personal financial management in a convenient manner given the uncertainty and lack of knowledge about the future (Mahapatra & Mishra, 2020; Statman, 2017; Thaler & Sunstein, 2021; Zhang & Sussman, 2018) which departs from a classical economic assumption of symmetric information among individuals. In addition, gains and losses are also viewed differently according to mental accounting theory. An individual is assumed to integrate multiple losses while segregating multiple gains. When a larger gain is faced with a smaller loss, the two are integrated, while when a larger loss is faced with a smaller gain, the two are segregated. The objective of this division is to maximise psychological pleasure and minimise pain (Kahneman & Tversky, 1979; Shefrin & Thaler, 1988; Townsend, 2018; Yeh, 2022).

Mental accounting behaviour clearly would have implications for decisions on savings and retirement wellbeing in general (Statman, 2017), given that mental accounting does have its pitfalls in that inefficient mental shortcuts taken by individuals to manage their finances may lead to bad financial decisions. However, it becomes more pertinent to pivot towards understanding retirement preparedness with the assumption that individuals generally exhibit mental accounting behaviour, as a lack of retirement savings may signal inefficient allocation of resources by individuals for their later years. As the relationship of mental accounting to savings behaviour, savings adequacy, and retirement preparedness can take many forms and is modestly understood within the context of the Malaysian population; machine learning which has been demonstrated to describe patterns and relationships in behavioural data can be used to understand this relationship in a more systematic and strategic manner as a complement and expansion of previous studies on retirement preparedness both locally and globally. This approach is also a review of existing relationships related to retirement preparedness which may bring about a deeper understanding of previously understood relationships.

1.2 Problem Statement

While understanding the absolute level of retirement preparedness among Malaysians is important and has been studied across multiple sections of the population with similar findings, i.e., modest levels of retirement preparedness, the study of retirement preparedness from the angle of behavioural economics (i.e.., mental accounting) remains limited**.** For instance, understanding individuals' allocation of wealth and expenditure into separate categories and how this can affect retirement preparedness may well serve as a benefit for policymakers to challenge existing notions on current policies' efficiency.

Despite most studies being able to demonstrate the existence of mental accounting behaviour in individuals (Antonides et al., 2011; Hoque, 2017; Mahapatra & Mishra, 2020), how mental accounting can underpin retirement preparedness remains limited, especially in Malaysia. In this regard, having a good overview of wealth and expenses can result in better personal financial management (Antonides et al., 2011; Hoque, 2017; Xiao & O'Neill, 2018). Through this finding, it can be implied that improved budgeting skills may spell a person having a higher chance of being prepared for retirement through better savings behaviour which leads to financial resource adequacy for retirement (Yeh, 2022). It is equally important and relevant to identify best mental account allocation recommendations which remain limited for this knowledge to be adapted by individuals in managing their finances. A good mental accounting allocation can only happen upon a better understanding of its weightage on retirement satisfaction.

In relation to segmental financial advice provided to Malaysians on retirement by professional licensed financial advisors and planners, it is noted that there is a limited focus on mental accounting behaviour in the training content for financial planners and advisors. Inculcating mental accounting in consultations with clients may be a factor that can lead to a person's success in meeting the goal of being well-prepared for retirement. For instance, clients may be advised to focus on accumulating one category of wealth before moving on to other types of wealth to ensure that wealth accumulation towards reaching retirement savings adequacy remains achievable and doable (Garnick, 2017). On top of this observation, there is an increasing call for behaviourally informed policies among Malaysians (Institute for Capital Market Research [ICMR], 2020; Perbadanan

Insurans Deposit Malaysia [PIDM], 2021). Further, practitioners in the financial planning industry would be empowered to give high-quality and behaviourally informed advice to clients upon a deeper understanding of mental accounting and retirement preparedness.

In relation to retirement studies, the usage of machine learning methods which is preferred for predictive analysis (Garibay et al., 2022), remains limited, where most studies opted for the usage of standard statistics. Given that machine learning plays a complementary role to standard statistics methods (Garibay et al., 2022), it is imperative that the retirement preparedness relationship in the presence of mental accounting be modelled using machine learning to be compared with the performance of other existing retirement preparedness models to ensure that necessary retirement policies are formed effectively. This is further substantiated by Sunstein (2021), where it was argued that once algorithms from machine learning are deployed, it can greatly reduce bias in modelling outcomes of the analysis. When an educator, researcher, financial service professional, lender, or policy maker needs to describe and/or predict a household's future financial situation, it was found that machine learning procedures can provide a robust, efficient, and effective analytic method (Heo et al., 2020). Advantages of machine learning include ability to handle complex and non-linear relationships between variables, process large-scale datasets with a significant number of variables and observations, effectiveness in handling missing data, and capability at analysing unstructured data types. In addition, the complementarity relationship between machine learning and behavioural economics is that behavioural economics provide testable hypotheses which help explain observed patterns of behaviour where machine learning describe patterns in behavioural data (Heal et al, 2022). Supervised machine learning emerges as an apt and compelling method for scrutinizing retirement behaviour, given its innate ability to discern meaningful patterns and intricate relationships within vast and intricate datasets. Its reliance on labelled training data equips it to accurately predict retirement outcomes, thus facilitating informed financial planning and robust policy formulation. The robustness of this approach in accommodating diverse input features and its capacity to generalize to novel data engenders dependable insights into retirement trends and preferences. Moreover, the interpretability of supervised models empowers researchers and stakeholders to gain deeper insights into the factors influencing retirement decisions, leading to targeted interventions and ultimately, augmenting retirement preparedness at a broader societal scale. Notwithstanding that, available built-in calculators across official banking and insurance websites for retirement neglect the need to consider subjective elements that make up a person's likelihood of attaining readiness for retirement, as it remains a challenge for a person to save even after knowing how much is needed to save for retirement.

1.3 Research Questions

Against this backdrop, three major research questions are posed for the purpose of this study. These are:

1. Does mental accounting exist in individuals?
2. Do mental accounting attributes have predictive power to retirement satisfaction?
3. How does pre-retirees' retirement thinking, and retirees' retirement satisfaction compare in terms of mental accounting attributes predictive power?

1.4 Research Objectives

The main objective of this study is to understand ways to enhance retirement preparedness among Malaysians in the presence of mental accounting. The objectives of this study relate back to the questions posed above. These are:

1. To explore the presence of mental accounting behaviour in individuals.

2. To examine the predictive power of mental accounting attributes in contributing towards retirement satisfaction.
3. To compare pre-retirees' retirement thinking, and retirees' retirement satisfaction compare in terms of mental accounting attributes predictive power.

1.5 Significance of Study

As the country moves and goes through a series of evolutions in terms of its economy, its population is poised to carry the burden of consequence if they are not equipped with the right level of retirement preparedness. With an increasing challenge in sustaining livelihood due to inflation, a person might not be able to take care of themselves should they not be able to sustain their consumption levels in the future, especially those who do not have adequate retirement savings.

The importance of knowledge of good savings behaviour via best mental accounting (i.e., allocation of wealth and expenditure that result in retirement satisfaction), which leads to savings adequacy and retirement preparedness, is imperative to reduce the future financial burden for the government arising from an inability to secure adequate financial resources. While this applies to every Malaysian, it must also be a focus for policymakers and financial planning practitioners where inculcating mental accounting in policy design and consultations is vital towards digitalising, democratising, and humanising retirement wealth accumulation experience by fellow Malaysians towards achieving readiness for retirement. As such, the significance of this study is to suggest meaningful ways to enhance the retirement savings ecosystem currently existing in Malaysia towards a more dynamic system which considers human elements that will encourage Malaysians to eventually be prepared for their retirement. Research in this study will show that different types of wealth and expenditure, as posited by the mental accounting category, have an impact on retirement where individuals can rank and invest in them towards becoming prepared for retirement. Conceptually, the findings is aimed at expanding the notion that allocation of wealth and expenditure according to mental accounting categories have impact on behavioural outcomes. Specifically, this study can be a foundational guide on the importance of best allocation of mental accounting attributes towards preparing for retirement (Garnick, 2017).

Practically, the study aims to provide a foundation for the tool of assessment or diagnosis for Malaysians to reduce financial pressure and advise Malaysians on the possible ways to achieve an adequate amount of savings for retirement. This is for prudent and sustainable financial health via best allocation of wealth and expenses into the non-fungible wealth and expenses mental accounting categories where current available tools may provide biased information, which may be of limited impact on encouraging Malaysians to have good savings behaviour, adequate saving, and eventually retirement preparedness. In essence, the predictive models developed from this study may provide a platform to guide individuals towards retirement preparedness. From a financial literacy perspective, the importance of saving in the best allocation (i.e., into different types of wealth accumulation channels) for retirement is envisaged. This will also be supplemented with a foundation for a tool of assessment for policymakers as an early warning system on the likelihood of retirement preparedness among various segments of Malaysians to reduce financial pressure on the government and produce necessary social protection policies for Malaysians.

In relation to these tools of assessment, the methodological significance of this study is to fill the gap where previous studies approached the topic of retirement preparedness using the standard statistical method, where this study intends to pursue the topic via machine learning. While machine learning plays a complementary role to standard statistics methods, the machine learning methods from this study can be used to compare with other studies where machine learning may have advantages over standard statistics methods.

In doing so, a calculated approach must be considered to ensure effective reach to all individuals in Malaysia. Various demographic factors such as gender, marital status, education level, and the number of dependents must be considered alongside factors of non-fungible wealth and expenses categories in coming up with the right strategy to address the lack of retirement readiness. Lastly, this study aims to provide insight and extend knowledge on which ways non-fungible wealth and expenses categories play in retirement preparedness.

1.6 Operational Definition for Key Terms

In this study, mental accounting relates to the perception of non-fungibility on otherwise seemingly equivalent options which is seen in the behaviour of allocating, organising, evaluating, earmarking of income and/or expenses into a set of categories In addition, gains and losses are also viewed differently where an individual is assumed to integrate multiple losses while segregating multiple gains. When a larger gain is faced with a smaller loss, the two are integrated, while when a larger loss is faced with a smaller gain, the two are segregated. In this study retirement preparedness is a status where it is conceptualised that being more prepared for retirement could take place upon having the best mental accounting allocations.

Retirement preparedness is defined as having the best mental accounting behaviour (not necessarily most efficient as per classical economic theory), as this can lead to retirement satisfaction. An optimised allocation of wealth and expenses according to mental accounting category would enable a person to be more prepared for retirement.

Retirement satisfaction relates to satisfaction in retirement life when compared to life during employment years.

Lastly, machine learning relates to developing and training a model with a learn training dataset first. Once the first stage is completed, the model is then tested with test dataset. Machine learning departs from standard statistical analysis in that the data from MARS wave 1 survey dataset is divided into training and test dataset (in 60:40 ratio, respectively).

CHAPTER 2 : LITERATURE REVIEW

2.1 Introduction

Given the long lineage of studies on retirement, a preliminary discussion consisting of factors that affect retirement preparedness is rendered pertinent towards the knowledge formation for this study. An overview of the previous studies that investigates the subjective and objective elements that determine retirement preparedness is pertinent to ensure that what are deemed important factors are considered in this study. Following this section, a discussion on global measurement tools for savings adequacy is conducted, as adequacy is inherently tied to retirement preparedness. An understanding of established benchmarks, tools, and measurements of adequacy is important towards understanding retirement preparedness is viewed in different jurisdictions.

Section 2.2 leads to viewing retirement preparedness globally with a special focus on the Malaysian context. Despite numerous developments, retirement preparedness levels are, at best, still modest. In response to this, a discussion on the psychological behaviour of mental accounting, coupled with other psychological behaviour theories deemed relevant towards understanding retirement preparedness, is conducted.

In relation to methodology, a brief discussion on previous methods employed to study retirement preparedness is conducted where it was understood that while many studies employed standard statistical methods, machine learning can be used as a complementary method to study retirement preparedness where the machine learning method is intended to narrow the gap in retirement studies. Following this, a section that discusses the machine learning method, as well as its benefits, is included. This chapter ends with the literature gaps identified in this study.

2.2 Factors that Affect Retirement Preparedness

Retirement Preparedness is theorised in the Life Cycle theory to encapsulate good savings behaviour that leads to adequate savings to sustain consumption levels in retirement (Modigliani & Brumberg, 1954). Therefore, good savings behaviour is an attitude an individual possesses in relation to managing their wealth to ensure that their financial security in retirement is not compromised. Adequate savings relate to having enough wealth to sustain consumption in retirement years. Several studies used savings adequacy as a proxy for retirement preparedness (Wang et al., 2021). A vast number of publications also looked at savings with the idea of achieving financial adequacy in a person's later years (Japelli & Modigliani, 1998; Japelli et al 2007; Japelli & Pistafferi, 2018)

Theories in relation to savings have been put forward many times, such as the Theory of Household Saving by Miller in 1963, which sought to establish a relationship between savings and consumption to income, prices of goods and services, as well as interest rates. The relationship between consumption and interest rates was also echoed in a paper by Smyth in 1993. An investigation by Juster and Taylor in 1975 relates the volatility of savings patterns in the post-World War United States, where the uncertainty element impacts savings behaviour. This laid the foundation for a further investigation of the psychological element in savings decision-making to take place in the form of the Behavioural Life Cycle hypothesis, where savings and consumption are dependent on the type of wealth, thereby recognising the presence of mental accounting behaviour in the decision-making process (Shefrin & Thaler, 1988). Further, in mental accounting theory, it is posited that individuals do not treat categories of wealth and expenditure as fungible and equal (Schooley & Worden, 2008; Shefrin & Thaler, 1988; Statman, 2017) where the implication of the mental accounting theory is the distortion of the marginal propensity to consume curve and savings allocation which would influence retirement preparedness (Xiao & Olson, 1993).

Separately, the savings pattern diverges depending on the behaviour of the consumer, where consumers with income uncertainty as well as being behaviourally impatient would use savings to buffer income fluctuations (Carroll, 1997). This finding was then also empirically tested by Jappelli et al. in 2007, where it was found to only apply to young consumers. The findings mentioned are further confirmed by an observation that low-income households generally have low savings globally (Dynan et al., 2004). This can be attributed to the fact that net disposable income for low-income households is low, and that income received is generally spent on inelastic necessity goods and services.

Aside from income, in a study conducted on Dutch households in 2016, factors such as demographics, skills, and education, including financial literacy, are known to be factors that influence savings behaviour (Brounen et al. 2016). Typical factors that influence savings behaviour, particularly in developing economies like Malaysia, include service quality, religious belief, and knowledge (Banerjee et al. 2021; Ismail et al., 2018). The inclusion of the financial literacy element runs consistent with a finding that higher financial literacy levels can improve savings adequacy and financial decision-making process (Hasler et al., 2022; Ismail et al., 2018; Lusardi, 2008; Song, 2020; Wang & Bartholomae, 2020;). In particular, it was found that demographic factors such as gender, race, income, number of dependents and level of education do influence the level of financial literacy (Mustapha & Jeyaram, 2015). A paper by Githui and Ngare in 2014 revealed that retirement preparedness is also influenced by financial literacy among demographical factors. This complements an earlier finding by Lusardi and Mitchell in 2011 that financial literacy is related to retirement planning or preparedness. Multiple studies undertaken on this topic agree with the notion that financial literacy, as well as its components such as awareness, capability, and knowledge on top of trust in institutions, affect retirement planning and preparedness (Banerjee et al. 2021; Clark et al., 2019; Galiani et al., 2022; Koh et al., 2021; Power & Hobbs, 2015; Segel-Karpas & Werner, 2014).

In emerging economies, it is noted that the rate of savings has been low, especially for retirement. This confirms a finding that Malaysians are generally not prepared for retirement (Asokumar & Jais, 2018). Separately, the tendency to simply leave future financial security to "fate" is apparent in certain communities that exhibit high adherence to tradition and culture. This would require a more refined nudge and consideration for psychological/behavioural factors to push members of communities to save for their future (Karlan et al, 2010; Madrian & Shea, 2001). This is consistent with a previous study which showed that cultural factors (religiosity bias) influence retirement preparedness among people of certain ethnicities in the United States (Blanco et al., 2017).

In response to the pressing need to encourage more savings, economists have highlighted the need for government action to address this issue (Asia Insurance Review, 2018). This comes at a time when savings are difficult due to the high cost of living and slow growth of income (Malaysian Financial Planning Council [MFPC], 2020).

However, in considering the wholesome picture of retirement preparedness, it was also argued that other resources, such as psychological, social, and health resources on top of savings adequacy, are important for a person to be prepared for retirement (Noone et al., 2010). In this regard, outlook and perception can be considered as psychological factors. Psychological factors that influence retirement savings and preparedness can also be augmented to include future time preference (which relates to exponential discounting in the future), retirement goal clarity, and self-rated financial knowledge. This is as it was found to mediate the relationship between demographic indicators and saving behaviours. In a study, individuals who engage in retirement planning (having positive time preference and being a planner) are better prepared to meet their retirement goals. Time preferences aside from financial literacy influence retirement preparedness (Clark et al., 2019; Goda et al, 2014). The importance of psychological factors in retirement preparedness is further compounded by several findings that mental health is important towards being prepared for retirement (Bogan & Fertig, 2018; Chen et al., 2018; Kim et al., 2016). These findings imply the importance of behavioural factors in addressing retirement preparedness in concurrence with educational push (Beshears et al., 2015; Beshears et al. 2012; Chetty et al., 2014; Crossley et al., 2014; Thaler & Benartzi, 2004). This would suggest that retirement experts would be well advised to consider using behavioural economics in conjunction with structural variables to achieve the maximum impact in addressing the retirement preparedness issue (Brown et al., 2008; Hershey et al., 2007). Some other psychological research on retirement was also underpinned by several psychological theories, such as rational choice theory, which ties workers' financial status to the external economic environment which will dictate their retirement. Image and Role theory relates workers' demographic status, work experience, marital life, type of industries and productivity to their retirement decision-making. Meanwhile, planned behaviour theory examines retirement decisions based on attitudes towards a job, employers, career, and workplace norms. Finally, expectancy theory ties workers' productivity, job characteristics, health status and subjective life expectancy to retirement decisions (Wang, 2013). In essence, factors that influence retirement preparedness are common and overlapping, as encapsulated in the table below:

Table 2.1: Retirement preparedness factors

Factors	Source

Demographics, income, skills, and education, including financial literacy and trust in institutions.	(Brounen et al., 2016; Clark et al., 2019; Githui & Ngare, 2014; Koh et al., 2021; Lusardi, 2008; Lusardi & Mitchell, 2011; Mustapha & Jeyaram, 2015; Power & Hobbs, 2015; Segel-Karpas & Werner, 2014)
Outlook (e.g., happiness or optimism) and perception (e.g., confidence or being realistic)	(De los Santos, 2019; Kim & Hanna, 2015)
Future time preference, retirement goal clarity, and self-rated financial knowledge.	(Clark et al., 2019)
Retirement-linked knowledge, expectations, attitudes, and planning behaviours.	(Leandro-França et al., 2016; Lusardi et al., 2020).
Mental health.	(Bogan & Fertig, 2018; Chen et al., 2018; Kim et al., 2016).
Services quality, religious belief, and knowledge.	(Ismail et al., 2018)
Social, psychological, physical, and mental health, as well as motivational resources.	(Noone et al., 2010; Yeung & Zhou, 2017)

2.3 Local and International Savings Adequacy Policies

In this study, the discussion on retirement savings adequacy takes from a micro-scale perspective, i.e., an individual person's savings. Savings adequacy is generally thought of as the amount of wealth enough to sustain a person's consumption in their retirement years (Wang et al., 2021). Having an adequate amount of savings will naturally render them financially prepared for retirement (Modigliani & Ando, 1957). While savings is used to measure retirement financial adequacy, it only forms one element towards becoming prepared for retirement as being prepared for retirement encompass having adequate mental, social, and psychological resources on top of financial adequacy (Noone et al., 2013). The measurement of adequacy has taken several paths and methods of assessment. Governments usually set a poverty threshold and/or minimum wage as a benchmark of an amount an individual or household needs as a guide to prevent poverty. Globally, the international poverty line was set at USD1.90 a day as of the year 2015, where this amount is considered enough on average to afford an individual's basic needs.

This ballpark figure has been revised from time to time (USD1.08/day in 1985 and USD1.25/day in 1993) to reflect the changing price of basic needs over time (Ferreira et al., 2016). As this measurement was derived based on the average poverty line across 15 low-income countries, a vast number of countries have established their own poverty line, which reflects the nuances of the economic reality of respective countries.

In the United States, the measurement of poverty is divided into two distinct measurements. In one, figures of poverty threshold provided by the Census Bureau are used for statistical purposes. The figures range from USD13,465 to USD50,035 depending on the age of the household head and the size of the household (US Census Bureau, 2021). Another set of measurement is more in-depth, where figures are adapted to suit the economy of different states within the United States. This was crafted generally for administrative purposes. In Malaysia, the minimum poverty line was set at RM2,208 (Department of Statistics Malaysia [DOSM], 2020). It is thought that if a person has enough savings to be able to receive a minimum amount of monthly income as per recommended and be above the poverty line, the amount of savings is considered adequate and able to prevent poverty (Ravallion, 1992).

While these recommended amounts by governments are useful to a certain extent, it does not consider the factors necessary for individuals to live meaningful lives, which include the financial capability to be full participants in society and the economy where the amount needed for this goes beyond the previously recommended minimum amounts. In the European Union, governments of member states adopted the At-Risk-of-Poverty and Social Exclusion Indicator (AROP) to measure and set a threshold for poverty. Generally, it is a percentage of a respective member country's median income which generally ranges from 40% to 70% (Eurostat, 2013). This measurement is considered more dynamic in that a single formula can be applied across member states. Additionally, with these considerations in mind, several organisations have considered setting another set of thresholds called living wages that hints at the amount necessary for individuals to lead meaningful lives (Chong & Khong, 2018).

These were recommended using calculations of the basket of goods and services a person needs based on their respective demographical background. A summary that encapsulates information from a few organisations which have introduced recommended amount of wealth; Malaysian citizens should have to sustain their livelihood is included in Table 2.2 below:

Table 2.2: Recommended amount of wealth for Malaysian citizens

Organisation	Details	Recommended Amount
Employees Provident Fund (EPF)	In a booklet issued in 2019, titled "Belanjawanku", a specific monthly amount was recommended for an elderly couple living in Klang Valley which can sustain expenditure on the products and services as below: • Food (RM850) • Housing (RM700) • Healthcare (RM130) • Transport (RM500) • Utilities (RM290) • Personal care (RM90) • Ad Hoc/One-Off (RM230) • Social Participation (RM170) • Discretionary expenses (RM130) The data for the calculation of the recommended amount was sourced from a survey of household expenditures, and a survey of prices of goods and services through catalogues, the internet, and at actual business premises between July 2017 and July 2018.	RM3,090 per month (or RM37,080 annually)
Bank Negara Malaysia	In a concept paper issued by the Malaysian central bank in 2018, a monthly amount was recommended for a couple without children in Kuala Lumpur based on a calculation of a basket of goods and services prices needed to sustain their livelihood. The goods and services included in the basket calculation are as below: • Food, housing, and transport • Recreation • Contributions to the Employees Provident Fund (EPF), income tax payable, and savings that could be used to meet an emergency spending, including an unexpected healthcare bill • Education and healthcare	RM4,500 monthly (or RM54,000 annually)

Table 2.2, continued

Organisation	Details	Recommended Amount
	The data on prices for the items above were sourced from the Department of Statistics Malaysia (DOSM), the Ministry of Domestic Trade, Co-operatives, and Consumerism (KPDNKK), and the National Property Information Centre (NAPIC) as of the year 2016.	
WageIndicator Foundation	WageIndicator uses prices from the Cost-of-Living Survey to calculate Living Wages in more than 70 countries. The Living Wage is an approximate income needed to meet a family's basic needs, including food, housing, transport, health, education, tax deductions, and other necessities. In 2019, it released a recommended amount for a typical Malaysian family (i.e., two adults and a number of children based on Malaysia's fertility rate from 2010 to 2014). The details of the goods and services basket are as below: • Food (RM1,090 to RM1,380) • Housing (RM570 to RM1,050) • Transport (RM200) • Healthcare (RM100 to RM200) • Education (RM200 to RM300) • Other expenses (RM110 to RM155) In a typical family, one adult is assumed to work full-time, and the employment rate of the other adult is derived from the national employment rate. The data for the calculation of the recommended amount were sourced from WageIndicator.org's in house survey, Cost of Living survey together with UN Food and Agriculture Organization (FAO), World Bank Databank Fertility rate 2010–2014 and International Labour Organisation Estimated participation rate in 2017.	RM1,419 to RM2,053 monthly (or RM17,028 to RM24,636 annually)

Regarding having a benchmark to indicate savings sufficiency, governmental organisations have also recommended replacement rates to ensure that consumption can be smoothened throughout a person's lifetime. Generally, savings are adequate when the amount can replace a portion of a person's salary. The salary can either be a person's last drawn salary or average career salary. A well-known replacement rate recommended by financial planning experts is usually 70% to 85% of a person's last drawn salary (Miller, 2017). This rule of thumb is supplemented with a recommendation by financial planners, which encourages an individual to have at least 3 to 6 months' worth of monthly salary in preparation for emergencies or financial shocks (Anong & DeVaney, 2010). Another minimum recommended amount by EPF for its members to have upon retirement is RM240,000 where the amount is based on the calculation of the minimum monthly pension payment for civil servants retiring at 55 years old with a life expectancy of up to 75 years old as per the average Malaysian life expectancy (Employees Provident Fund [EPF], 2018). The most recent amount was increased to RM600,000 (Romadan, 2022), due to changes in the price of goods and services.

While heuristics (also known as a mental shortcut) is the go-to method in analysing as well as providing a benchmark of what constitutes savings adequacy, other studies have approached the subject in innovative ways. In a study by Chybalski & Marcinkiewicz (2015), the replacement rates (thumb rules) used were found to be unreliable to be a guide towards achieving savings adequacy. The heterogeneity of what constitutes adequacy to individuals led to the findings by Chybalski & Marcinkiewicz (2015), where the adequacy of pension amount was measured with consideration to several factors such as prevention of poverty on top of consumption smoothing while eliminating any differences between genders. These findings formed the synthetic pension adequacy indicators (SPAI1-3).

It is imperative that each state government within Malaysia have an adequacy benchmark as a localised measure of the savings adequacy rate in the state. This is because the cost of living is different in each state, which impacts the cost of the standard basket of goods and services in the state. The measure can also be used to craft a contextualised living wage standard for fellow citizens to ensure that equity is achieved within the context of different economic circumstances of each state.

In Malaysia, several savings calculators are made readily available online for the public to analyse for themselves to see if they have enough saved for retirement. Generally, these calculators would require self-reported figures such as income, savings, and age to provide an estimation of future savings with embedded assumptions such as inflation and investment return rates in the calculations. Information on several of these calculators is presented in Table 2.3 below, accurate as of April 2022:

Table 2.3: Commercial retirement calculators

No.	Calculator	User-directed self-reported figures	Outcome	Source
1	Retirement Savings Calculator	• Initial Deposit (RM); • Annual Interest Rate (%); • Years; • Frequency of Recurring Savings; and • Recurring Deposit Amount (RM)	Report of final savings amount (RM)	CALCULATOR.COM.MY (independent website)
2	Savings Plan Calculator	• How much do you want to save, based on today's cost of living (RM)?; and • How many years are you planning to save to reach your goal?	Report of recommended monthly savings amount (RM)	Great Eastern (insurance company)
3	Retirement Calculator	• Age; • Current salary (RM); • Employee Provident Fund's balance (EPF) (RM); and • Private Retirement Scheme balance (RM).	Report of savings amount required for retirement to last up to 80 years old from retirement at 60 years old vis-à-vis current retirement savings (RM).	Private Pension Administrator (central administrator for the Private Retirement Schemes)
4	Retirement Goal Calculator	• Current age; • Expected age of retirement; • Expected age of complete use of retirement funds; • Expected expenses amount in retirement (annual and monthly); • Assets set aside for retirement (cash, investments, endowments, property for rent or sale, EPF current balance and monthly contribution)	Amount of savings needed for retirement (RM). Expected surplus or deficit in retirement savings (RM).	Oversea-Chinese Banking Corporation (Malaysia)

Table 2.3, continued

No.	Calculator	User-directed self-reported figures	Outcome	Source
5	Retirement Planning Calculator	• Current age; • Desired retirement age; • Life expectancy; • Expected annual expenditure in retirement (RM); • Expected inflation rate; • Expected rate of investment return; • Current retirement plan 1 (EPF current balance, annual contribution, increment to annual contribution, expected rate of EPF investments return) • Current retirement plan 2 (Fixed deposits current savings, annual contribution, increment to annual contribution, expected rate of fixed deposit investments return); • Current investments 1 (equity fund current investment, annual contribution, increment to annual contribution, expected rate of equity fund investments return) • Current investments 2 (bond fund current investment, annual contribution, increment to annual contribution, expected rate of bond fund investments return) • Current investments 3 (Other assets available at the age of 60, which may include property, insurance policies, annuities, etc.) • Risk profile (very low to very high)	Recommended amount needed for retirement (RM); Projected amount of savings in retirement (RM); Status of retirement savings amount (surplus or deficit); Amount of savings in today's terms and future terms (RM).	Affin Hwang Capital Asset Management (Malaysia)

Table 2.3, continued

No.	Calculator	User-directed self-reported figures	Outcome	Source
6	Retirement Calculator	• Current age; • Expected Retirement Age; • Monthly EPF Amount Contribution (RM); • Current EPF Amount Available (RM); • Expected EPF rate of return; • Expected Salary Increment Rate; • Expected Inflation Rate; • Current Annual Expenses (RM); • Current lump sum Savings Available (RM) (including expected rate of return); • Current monthly savings available (RM) (including expected rate of return); • Current yearly savings available (RM) (including expected rate of return) • Expected annualised rate of return on retirement income; • Expected Total Saving Upon Retirement (RM) • Expected EPF Amount Upon Retirement (RM) (55 years old or above)	Capital Consumption Table After Retirement	Kenanga Investors Berhad
7	Retirement planning calculator	• Current age; • Retirement age; • Estimated life expectancy; • Inflation rate; • Investment rate of return until retirement; • Investment rate of return during retirement;	Future Amount of Expenses at Retirement Future Amount Required for Retirement Fund Future Value of Investments Earmarked for Retirement Fund; Shortfall of Future Amount	Public Mutual Berhad (Malaysia).

Table 2.3, continued

No.	Calculator	User-directed self-reported figures	Outcome	Source
7		• Current annual net income • Estimated annual salary growth rate • Current annual expenses.	Required for Retirement Fund Current Lump Sum Investment or Current Level Monthly Investment	
8	Financial Goal Simulator	• Current age; • Expenses amount in retirement (RM); • Amount of current retirement savings (RM); • Monthly retirement savings (RM).	Projected amount of personified adequacy of savings (RM).	Maybank Berhad (Malaysia).

2.4 Retirement Preparedness Trend and Developments

Retirement Preparedness is the level of readiness or preparation towards retirement. One important form of measurement of retirement preparedness is by heuristics, i.e., retirement replacement rates which is the ratio of post-retirement income over pre-retirement income. While not the only yardstick for measuring retirement preparedness, it has been employed with varying popularity across the world, with many recommending about 70% replacement rate to be the suitable amount for those about to enter retirement. In this view, retirement preparedness is equated to savings adequacy. The Congress of The United States Congressional Budget Office released a primer in 2017 on retirement savings adequacy, which revealed that studies mostly measure adequacy from a year-to-year perspective or multiyear approach, which generally requires complex projections and more detailed data. Heuristics (or mental shortcut) are preferred, seeming that it is easily understood and eases the process of saving towards retirement (Chybalski & Marcinkiewicz, 2016; Miller et al., 2017). Despite that, many studies have proven that individuals did not have adequate savings to achieve recommended replacement rates for their retirement years (Crawford & O'Dea, 2020; Kim & Hanna, 2015; Poterba, 2015).

However, there are also several index measurements developed to capture the complexities of measuring retirement preparedness beyond adequate savings. From an industry perspective, a retirement readiness index was developed by Aegon in 2022, where the Aegon Retirement Readiness Index (ARRI) assesses and quantifies levels of retirement awareness and savings behaviour. On a scale of 1–10, the score encapsulates, among others:

- Personal responsibility for income in retirement

- Level of awareness of the need to plan financially for retirement.
- Financial capability/understanding of financial matters regarding plans for retirement.
- Retirement planning — level of development of plans.
- Financial preparedness for retirement; and
- Income replacement — level of projected income replacement.

According to Aegon, it was found that individuals across the globe generally are only minimally prepared for retirement, given the aggregate score of 6.2, which indicates a medium score. Although growth was seen from year to year, most individuals seem to still be on the mediocre scale, which at best would only render them as minimally prepared for retirement. While this might vary when controlling for gender, age, income level, and nationality, among others, generally, it is well understood that the level of preparedness for retirement remains modest across the board.

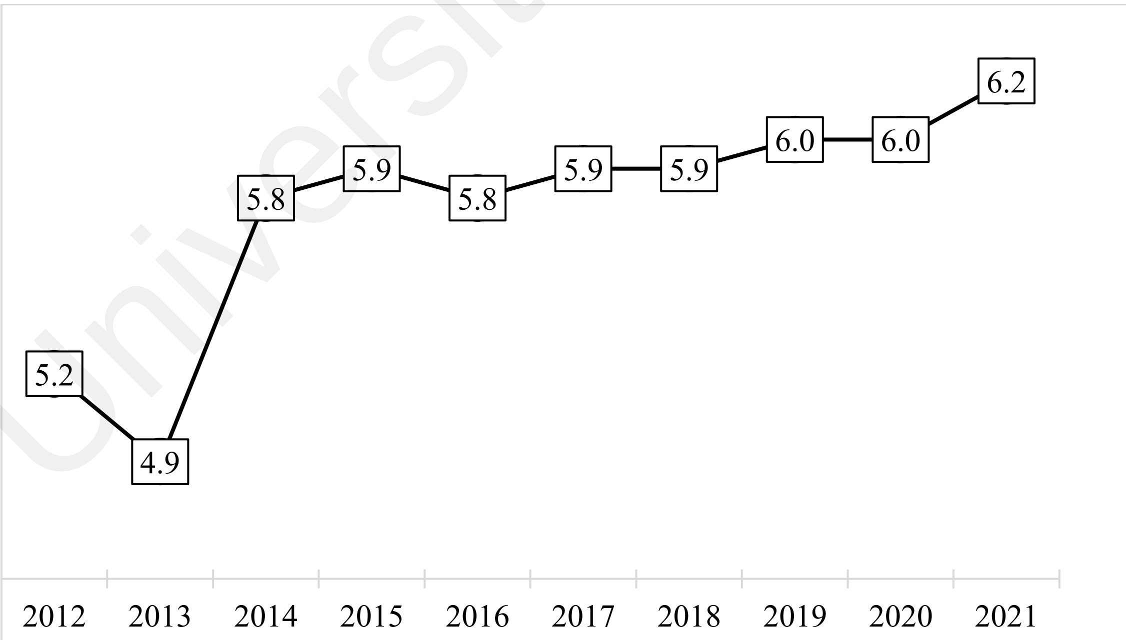


Figure 2.1: Year to year Aegon global retirement readiness index growth

Another joint study by AustralianSuper, which is Australia's largest Australian superannuation and pension fund with Monash University, developed the retirement confidence index in 2017. Retirement confidence was treated as equal to retirement preparedness in this study. The index captures individuals' perspective of being prepared for retirement, which extends beyond financial means such as awareness and skills, social factors, health, and wellbeing as well as retirement planning. In 2021, the findings from the index indicated that Australians, on average, may only have adequate savings for a modest retirement at best, where the amount was found to be not adequate to sustain a comfortable retirement (Ghafoori, 2021). The element of confidence in retirement was further echoed in several studies which focused on subjective assessment of retirement preparedness, where it was found that confidence does play a role towards better preparation for retirement (Angrisani & Casanova, 2021, Kim & Hanna, 2015).

Where studies on retirement preparedness entail a review of the ability of individuals or households to achieve an acceptable and reasonable replacement rate for retirement years, many studies were dedicated towards studying preparedness from a psychological point of view (Bogan & Fertig, 2018; Clark et al., 2019; Chen et al., 2018; Hershey et al., 2007; Kim & Hanna, 2015; Kim et al., 2016; Leandro-França et al., 2016). In a study conducted in Israel, it was argued that being psychologically prepared would entail actual preparedness for retirement, yet many respondents were found not to be prepared for retirement (Segel-Karpas & Werner, 2014). However, this study had a limitation as it uses cross-sectional data, which would make it hard to establish the direction of causality. A study conducted in Brazil produced similar results where respondents felt confident of their preparation level for retirement, which can be due to the straightforward method for saving for retirement, which is not the case in many developed countries such as the United States (Franca & Hershey, 2018). This also comes at a time when a separate study proved that being financially prepared for retirement induces positive feelings of being prepared for retirement (Yeung, 2013).

In the United States, it was found that many individuals are not prepared for retirement (Wang et al., 2021). This is in tandem with the finding that Americans are not financially literate (Lusardi & Mitchell, 2007). This is more pronounced among members of ethnic communities such as Latino Americans, who were found to be less prepared for retirement as they rely more on traditional family structure for support in the later years while leaving their future to chance (Blanco et al., 2017). This finding on Latino Americans is consistent with those in emerging economies. This is also echoed in another study conducted in Saudi Arabia, where Saudi Arabians were found to be unfavourable towards retirement, and despite being worried about being financially unprepared for retirement, they lack financial planning (Diaw, 2017).

At this juncture, retirement preparedness and retirement planning are two distinct yet interconnected concepts that play crucial roles in an individual's financial journey. Retirement preparedness refers to the overall state of being ready for retirement. It encompasses various aspects of financial stability and personal well-being necessary to sustain a comfortable lifestyle after leaving the workforce. This includes having a sufficient retirement savings fund, managing debts and expenses, maintaining good health, and establishing a suitable support network. Retirement preparedness involves taking proactive steps to ensure a secure and fulfilling retirement, considering factors such as income sources, investment strategies, insurance coverage, and long-term care arrangements.

On the other hand, retirement planning focuses on the specific strategies and actions employed to achieve retirement preparedness. It entails creating a comprehensive roadmap that outlines the financial goals and objectives for retirement, as well as the steps needed to reach those goals. Retirement planning involves assessing one's current financial situation, estimating future income needs, identifying potential sources of income (such as pensions, social security, or investment returns), and formulating a saving and investment strategy to accumulate the necessary funds. It also includes considerations such as tax planning, estate planning, and determining the optimal age to retire.

Both retirement preparedness and retirement planning are integral to ensuring a smooth transition into retirement (Lusardi, 2008; Lusardi & Mitchell, 2007, Lusardi & Mitchell, 2011). While retirement preparedness represents the overall state of readiness, retirement planning is the active process of developing a personalized roadmap to achieve that readiness. By carefully considering and implementing these two aspects, individuals can work towards a secure and enjoyable retirement lifestyle.

2.4.1 Retirement Preparedness in the Malaysian Context

In emerging economies, retirement preparedness is also noted to be low, given the lack of financial literacy and strong financial infrastructure. It is noted in a study by the Malaysian Financial Planning Council (MFPC) in 2018 that Malaysians generally save for other future obligations first while saving later for retirement. In other words, Malaysians generally do not find saving for retirement to be a top financial planning priority. This could affect their retirement preparedness level as the amount they would have saved for retirement and, subsequently, the amount of money at their disposal in retirement would be low. Malaysians, in general, struggle to save for their retirement (Imran et al., 2021; Zainal Alam & Yong, 2021), as evidenced by the fact that as of the year 2021, only 3% of Employees Provident Fund (EPF) contributors did achieve the level of basic savings by retirement age (EPF, 2021). While this evidence comes at a time of health and economic crisis brought about by the Corona Virus Disease 2019 (COVID-19) pandemic, the lack of retirement savings issue pre-dates the crisis (Khazanah

Research Institute, 2021). Malaysia stands at an inflection point where its population is undergoing rapid ageing while the labour sector is experiencing a surge in self-employment due to the drastic growth and adoption of technology. This comes at a time when financial literacy is at a low level, and the amount of savings for retirement is not enough together with the existing structure for retirement savings which often does not include self-employed workers who are increasing in numbers in Malaysia (Zainal Alam & Yong, 2021). This is compounded by the fact that different age cohorts have different retirement investment, savings, and consumption behaviours at a time when the older generation is living longer and outliving their assets while the younger generation has a higher incidence of bankruptcy, whereas, in 2019, 1 in every 4 bankruptcy cases are from those of the ages 25 to 34 years old (Malaysian Department of Insolvency, 2019).

While the rate of savings among Malaysians has been historically on the low side (Khazanah Research Institute, 2020), the COVID-19 pandemic brought new concerns, given the contraction of global economic growth and rising unemployment rate. The impact of COVID-19 on Malaysians is compounded by a finding in a recent survey conducted by the Department of Statistics Malaysia (DOSM), where most working Malaysians have savings equivalent to less than 2 to 4 months' worth of their monthly salary (Goh, 2020). This goes against the rule of thumb recommended by financial planners, which encourages an individual to have at least 3 to 6 months' worth of monthly salary in preparation for emergency or financial shocks (Anong & DeVaney, 2010). It is imperative that the construction of an internationally accepted retirement preparedness index become available as a minimum benchmark for countries to measure the state of retirement preparedness of their respective population while adopting and adapting the best standards from countries whose populations are well prepared for retirement. Table 2.4 summarises different conceptual definitions of retirement preparedness from several recent studies.

Table 2.4: Retirement preparedness definitions

No	Source	Definition	Category
1	(Aegon Corporate, 2022, p. 6)	"…behaviours towards their own planning and saving, as well as how on course they were to achieve their desired replacement income."	Behaviour, Ability
2	(Kim & Hanna, 2015, p. 2)	"Retirement savings adequacy as a benchmark."	Adequacy
3	(Lissington et al., 2016, p.11)	"…financial preparedness for retirement."	Adequacy
4	(Goldman, 2018, p.10)	"…expectations for retirement, preparations to retire, retirement risks and whether they have planned for longevity (i.e., an especially long life), chronic ill health, and a drop in the value of their assets."	Behaviour, Adequacy, Ability
5	(Angrisani & Casanova, 2021, p. 5–6	"…positive net financial wealth, stock ownership, positive IRA wealth, type of pension plans the respondent has access to through their employer."	Ability, Adequacy
6	(Wang et al., 2021, p. 599)	"…retirement planning, retirement saving, retirement plan: employer-based or individually held, and investments."	Behaviour, Adequacy
7	(Ghafoori, 2021, p. 2)	"…feeling prepared and ready to make the transition to retirement or feeling prepared and confident during the retirement experience."	Psychology
8	(Catalano, 2021)	"Financial readiness is only one part of being prepared for retirement. Being prepared mentally, socially, emotionally, and physically are also important."	Behaviour, Adequacy, Ability, Psychology
9	(Gornick & Sierminska, 2021, page 2)	"…as the capacity of households to have accumulated wealth that will allow them to sustain their income level 'near the age of retirement', for a period of time."	Ability, Adequacy
10	(Hasler et al., 2022, p. 4)	"…two indicators of retirement readiness: retirement planning and saving for retirement."	Behaviour, Ability, Adequacy

2.5 Pre-retirees' Retirement Preparation

Pre-retirement preparation is an essential aspect of retirement planning that helps individuals to transition smoothly from their working life to retirement. Retirement preparation involves various activities such as financial planning, health planning, and psychological preparation. This paper discusses pre-retirees' retirement preparation and the importance of family involvement, retirement age, access to retirement information, and pre-retirement planning activities.

Family involvement is an essential aspect of pre-retirement preparation. According to Olatomide et. al (2012), family involvement is indispensable in pre-retirement preparation. The study found that family involvement in pre-retirement preparation helps to reduce anxiety and stress associated with retirement. Family members can provide emotional support, help with financial planning, and offer advice on post-retirement activities. Therefore, pre-retirees should involve their family members in their retirement planning process.

Retirement age is another critical factor in pre-retirement preparation. Freed et al (2016) found that only 12% of general pediatricians plan to retire before the age of 60, while 56% plan to retire at age 65 years or older. The retirement age is essential because it determines the amount of retirement resources an individual can accumulate. Therefore, pre-retirees should plan their retirement age to ensure that they have enough retirement resources to sustain their post-retirement life.

Access to retirement information is also crucial in pre-retirement preparation where it was found that those who believe that they know more about financial planning are more likely to have prepared for retirement (Thuku, 2013). Therefore, pre-retirees should have access to retirement information to help them make informed decisions about their retirement planning. Retirement information can be obtained from various sources such as retirement seminars, financial advisors, and online resources. Further, simplification of retirement planning can enhance retirement savings (Beshears et al., 2006).

Pre-retirement planning activities are also essential in retirement preparation as it was found that pre-retirement planning activities can help increase the amount of retirement resources in various domains. Pre-retirement planning activities include financial planning, health planning, and psychological preparation. Financial planning involves saving for retirement, creating a budget, and investing in retirement accounts. Health planning involves taking care of one's health to ensure a healthy post-retirement life. Psychological preparation involves preparing for the emotional and psychological aspects of retirement (Yeung & Zhou, 2017).

In conclusion, pre-retirement preparation is an essential aspect of retirement planning that helps individuals to transition smoothly from their working life to retirement. Family involvement, retirement age, access to retirement information, and pre-retirement planning activities are critical factors in pre-retirement preparation. Pre-retirees should involve their family members in their retirement planning process, plan their retirement age, have access to retirement information, and engage in pre-retirement planning activities to ensure a successful retirement.

2.6 Retirees' Retirement Satisfaction

Retirement satisfaction is an essential aspect of retirement planning that determines the quality of life of retirees. Retirement satisfaction is influenced by various factors such as personal factors, family situation, circumstances in which the transition from work to retirement occurred, motivation, personality, financial planning, health, and leisure activities. This paper discusses retirees' retirement satisfaction and the factors that influence it.

According to Floyd et. al (1992), retirement satisfaction is assessed based on six areas: preretirement work functioning, adjustment and change, reasons for retirement, satisfaction with life in retirement, current sources of enjoyment, and leisure and physical activities. The study found that retirees' satisfaction with life in retirement is influenced by their adjustment and change, reasons for retirement, and current sources of enjoyment.

Retirees' level of retirement satisfaction depends on personal factors such as health and wealth, family situation, and circumstances in which the transition from work to retirement occurred (Potocnik et al, 2011). The study found that retirees who have good health and wealth, a supportive family, and a smooth transition from work to retirement are more likely to be satisfied with their retirement life.

Retirees' motivation is also an essential determinant of satisfaction with life in retirement (Stephan et al, 2008) The study found that retirees who are self-determined and have a sense of control over their lives are more likely to be satisfied with their retirement life.

Retirees' personality is another factor that influences retirement satisfaction where Reis and Gold (1993) found that retirees who have a positive personality, such as being optimistic and having a sense of purpose, are more likely to be satisfied with their retirement life.

Financial planning and expectations also play a crucial role in retirement satisfaction as it was found that retirees who have good financial planning and realistic expectations about their retirement life are more likely to be satisfied with their retirement life (Bender, 2012). In addition, leisure activities are also essential in retirement satisfaction as it was found that retirees who participate in leisure activities are more likely to be satisfied with their retirement life (Krahe, 2011).

Retirement satisfaction is not only influenced by personal factors but also by family factors, according to Smith & Moen (2004). The study found that retirees' spouses' satisfaction also affects their retirement satisfaction. Couples who report joint satisfaction are more likely to be satisfied with their retirement life.

Finally, Sigauw (2017) found that retirees' satisfaction with life is influenced by various factors such as self-efficacy, health, income, confirmation of retirement expectations, ageism, retirement planning, and conditions of exit.

In conclusion, retirement satisfaction is an essential aspect of retirement planning that determines the quality of life of retirees. Retirement satisfaction is influenced by various factors such as personal factors, family situation, circumstances in which the transition from work to retirement occurred, motivation, personality, financial planning, health, and leisure activities. Retirees should consider these factors to ensure a satisfying retirement life.

2.7 Mental Accounting as a Financial Management Behaviour

Behavioural Life Cycle Theory, developed by Shefrin and Thaler in 1988, paved the way for Mental Accounting theory, which forms the basis of this study's framework. In the traditional Life Cycle model setting, good savings behaviour leads to an adequate amount of savings to sustain consumption levels in retirement (Modigliani & Brumberg, 1954). The Behavioural Life Cycle hypothesis (Shefrin & Thaler 1988), which led to mental accounting theory, posits that people mentally frame wealth as belonging to either current income, current asset, or future income. This consequently has implications for their behaviour as the accounts are largely mentally considered as non-fungible and the marginal propensity to consume out of each account is different. The categories of wealth into the three mentioned categories were found to be exhibited in the mental accounting behaviour of Indian households (Mahapatra & Mishra, 2020). The Behavioural Life Cycle Theory was developed at a time when behavioural economists argued that humans find it difficult to estimate their life-cycle wealth, longevity, and future spending needs because humans struggle to reconcile the desirability of saving when the income is high with a stronger temptation to spend (Statman, 2017). In return, humans conduct mental accounting as a form of self-control mechanism. This also follows the weak support for the Life Cycle Hypothesis and strong support for hyperbolic discounting theories (the tendency for people to increasingly choose a smaller-sooner reward over a larger-later reward as the delay occurs sooner rather than later in time) by Bernheim et al. in 2001 where decisions made in relation to retirement wealth and savings were more in line with perceived “rule of thumb” and “mental accounting” rather than the expectation of complete rationality from agents.

In the Behavioural Life Cycle, behavioural elements such as self-control, mental accounting and framing are inculcated in the Traditional Life Cycle Hypothesis. Broadly, mental accounting theory consists of several elements, many of which are based on the mental division of economic categories but do not necessarily pertain to mental budgeting. Hedonic editing, classification of profits and losses (money received and paid), earmarking and labelling of income and assets, simultaneous borrowing and saving, and mental budgeting are some of these features. However, this study will move forward focusing on the narrow sense of mental accounting, i.e., the behaviour of different value perceptions of gains and losses on top of categorising wealth and expenditure. For example, faced with the choice of 100% of winning RM50 or a 50% chance of winning RM100, humans will always be loss averse and choose the first choice despite the probabilistic outcome of the two options being the same. This behaviour is consistent with the mental mechanism of viewing types of wealth and expenditure differently (Thaler & Sunstein, 2021). The dominating concept in the mental segregation of wealth and expenditure and different valuation of gains and losses is the non-fungibility of equivalent options. For segregation of mental accounts, all accounts should reap the same utility (in a perfect financial market, that is) while the same applies to gains and losses where the amount of disutility felt in a loss should be equal in magnitude to the utility felt in a gain. However, this is not the case due to the loss-averse behaviour humans exhibit.

The mental accounting theory's assumptions are that households treat components of their wealth as non-transferable (non-fungible). Assets are, therefore, not easily interchangeable with other types of assets, even in the absence of credit rationing. This departs from the traditional Life Cycle Hypothesis, which assumes one type of asset throughout a person's lifetime. Wealth is framed into three subcategories, i.e., current income (such as cash, checking accounts, and money market accounts), current assets (such as savings accounts, unit trust funds, and other capital market products), and future income (such as home equity and retirement savings) (Schooley & Worden, 2008). The mental framing or budgeting of wealth is done to manage the difficulty agents face in managing their finances to avoid the risk of running out of money before their eventual death (Antonides & de Groot, 2022; Statman, 2017;). The current income of a person faces the highest temptation to be used, with the future income facing the least temptation. In this regard, expenses are also categorised into necessities, discretionary and luxury items (Statman, 2017).

In this theory, self-control is the cost of forgoing instant succumb to temptation. The element of self-control is important, given its high correlation with savings (Rha et al., 2006). Higher temptation can be managed with higher self-control. An example of self-control is the cost of forgoing immediate spending to save for future consumption. Mental accounting simply means a person would find one type of wealth more tempting to be used than other types of wealth. In this case, current income is more tempting to be used rather than current assets. Mental accounting would cause wealth to be categorised into sub-categories where one type of wealth is not changeable to another type of wealth (Shefrin & Thaler, 1988). Framing is the saving rate that can be affected by the way in which increments to wealth are framed. For example, an increase in regular income is treated differently than an anticipated bonus. In addition, gains and losses are also viewed differently according to prospect theory developed under mental accounting theory (Kahneman & Tversky, 1979; Shefrin & Thaler, 1988; Townsend, 2018; Yeh, 2022). An individual is assumed to integrate multiple losses while segregating multiple gains. When a larger gain is faced with a smaller loss, the two are integrated, while when a larger loss is faced with a smaller gain, the two are segregated. The objective of this division is to maximise psychological pleasure and minimise pain.

Several studies have documented the impact mental accounting has on spending and savings behaviour. In relation to household savings, it was also suggested that employing mental budgeting was considered part of financial behaviour (Van Raaij et al., 2020). In a study by Antonides et al. in 2011, it was found that the behaviour of mental accounting (interchangeable with mental budgeting in this study) was found to be positively associated with having an overview of expenses and current accounts and household financial management (Antonides et al., 2011; Hoque, 2017). Thus, it can be implied that good mental accounting behaviour leads to good savings behaviour (Mahapatra & Mishra, 2020). In view of mental accounting's effect on expenses, it was also suggested that it might relate to savings behaviour (Antonides et al., 2011; Strömbäck et al., 2017; Strömbäck et al., 2020), as mental accounting behaviour is used as a tool for self-control (Cheema & Soman, 2006; Wertenbroch, 2003, as cited in Antonides et al., 2011), especially with low-income individuals. Echoing previous findings, mental accounting behaviour was also observed in non-monetary resources, where smallholder farm households in China were found to have exhibited mental accounting behaviour in rationing their own produce for consumption. The behaviour was seen despite the production of their own food since the smallholder farm households were from the low-income group (Huang et al., 2020). The finding by Huang et al. (2020) was also expanded by Hoque (2017) that mental budgeting has a significant positive influence on the financial management of small and medium business owners. As mental accounting is considered a self-control device, it was also found that people with a lack of self-control exhibit flexibility in designing mental accounting categories (Cheema & Soman, 2006). The findings imply that individuals do practise mental budgeting regardless of self-control levels, but with varying degrees of flexibility in designing their mental accounts.

In relation to the demographic background, it was found that females were more likely to be associated with the usage of mental accounting strategies, where mental accounting strategies were found to be dependent on individuals' traits (Antonides et al., 2011; Muehlbacher & Kirchler, 2013). The gender factor is consistent with Agnew et al. (2008) and Ashraf et al. (2006). However, it was also suggested that mental accounting behaviour is a trait that is opposed to rationality, where it was found that females were less likely to employ mental accounting, given that females were found to be more rational than men (Li, 2021). Further, it is agreed that higher financial literacy reduces mental accounting behaviour (Li, 2021); where this is echoed by Huang et al. (2020), where more experience in dealing with a specific resource will cause less practice of mental accounting. Due to its strong association with financial behaviour, it was suggested that better mental accounting should be trained in favourable mental tax accounting practices to foster voluntary compliance, especially for an inexperienced self-employed worker (Muehlbacher & Kirchler, 2013).

In relation to retirement preparedness, Garnick (2017) published a white paper which explains that young adults would best allocate wealth to one category of mental accounting (for instance, the current assets category) before focusing on the next category (for instance, future income category) instead of opting to diversify wealth into separate categories all at once. However, it was also argued that mental accounting, if practised all the way into retirement, may hamper consumption in tandem with declining cognitive ability associated with ageing (Benz, 2013).

In Malaysia, a report published by Perbadanan Insurans Deposit Malaysia (*Malaysian Deposits & Insurance Corporation*) (PIDM) and The Behavioural Insights Team (BIT) in 2021 identified behavioural insights around savings and insurance behaviours among Malaysians. In their report focusing on savings, mental accounting behaviour is touted to be leveraged to increase debt repayment despite acknowledging that mental accounting may lead to negative consequences in relation to owing debt. In this regard, it is possible to train better mental accounting towards better financial management and savings behaviour. A report by the Institute of Capital Market Research Malaysia in 2020 echoed the PIDM's report, which recommended that policymakers would be better off to leverage on mental accounting to enhance savings rates among Malaysians by inculcating mental accounting elements in financial product designing via the digitalisation of wealth management. In relation to retirement behaviour in Malaysia, a study adopted mental accounting theory as the theory is assumed to indicate awareness of financial management. It was found that individuals who exhibit mental accounting save presently to ensure retirement goals are achieved (Lim et al., 2021).

Despite its high correlation with financial behaviour, perceived usefulness in understanding preferences as well as positive savings behaviour (Mahapatra & Mishra, 2020), it was observed that mental accounting as a financial behaviour is not included in the Malaysian Financial Planning Council (MFPC)'s financial planning syllabus while mental accounting was understood to be discouraged according to Module 1 of Financial

Planning Association of Malaysia (FPAM)'s syllabus[1]. This implies that licensed and certified financial planners in Malaysia, in practice, are minimally trained to inculcate better mental accounting elements in their advice to clients.

2.8 The Theory of Reasoned Action (TRA) and the Theory of Planned Behaviour (TPB)

The TRA and TPB are related in that the latter builds on the former. The TRA explains the relationship between attitudes and behaviours, as well as relationships between users of technology and the technology itself. An individual's positive or negative feeling (evaluative effect) relates to performing the target behaviour, which includes the person's perception of the people who are important to him and their thoughts on whether he should or should not perform the behaviour in question. The theory only applies to behaviour that is consciously thought out beforehand. Irrational decisions, habitual actions, or any behaviour that is not consciously considered cannot be explained by this theory (Ajzen & Fishbein,1980).

The TRA presupposes that the behaviour is under volitional control, where individuals believe they can perform the activity whenever they choose to. Gradually, the TRA became more popular for studying behaviours in which control was a variable aspect. The TRA was supplemented for this purpose with a component known as perceived behavioural control. This idea describes the degree to which people believe they can accomplish the behaviour because they have appropriate capabilities and/or opportunities. It is easy to see how this component can significantly improve the model's universality of applicability because many behaviours require specific abilities or external facilities. For example, usage of public transportation would remain limited if there is a lack of first-

[1] MFPC and FPAM are the only two certifying institutions for the financial planning profession in Malaysia.

mile and last-mile connectivity availability, and abandoning private cars is often impractical, at least when public transportation functions poorly. The successor of the TRA that incorporates volitional control is the TPB.

The TPB postulates an individual's intention to perform an accepted or given behaviour (Ajzen, 1991), and it was claimed that it is one of the best-suited theories used to predict and understand human behaviour especially relating to financial behaviour (Xiao, 2008).

From its inception, the TPB has been used by several scholars across different disciplines such as family planning, weight loss, voting, alcoholism (Ajzen & Fishbein, 1980) and in consumer behaviour-related studies on the mortgage, credit counselling and investment decisions (Xiao, 2008). Also, from previous empirical studies, it was found that the theory has been well supported by those studies (Ajzen, 1991; Armitage & Conner, 2001).

As per Ajzen (1991), a person's behaviour is influenced by his or her behavioural intention, which is determined by attitude, subjective norm and perceived control. As summarised by Xiao (2008), the theory emphasised the factors of an individual's actual behavioural choices where the individual will demonstrate an attitude toward the forthcoming behaviour based on the evaluation of such behaviour, which is backed by the person's perception of the outcome of such behaviour. In other terms, a person will always assess the outcomes of a behaviour and that assessment shapes the person's attitude towards that behaviour.

Following the basics of the theory and its applicability to retirement preparedness, it is understood that an individual will not demonstrate an accepted financial behaviour unless the value of such behaviour is being perceived by the person as positive, which can be captured from his or her attitude towards that behaviour and the individual's personality. Hence, it can be argued that even if an individual possesses financial knowledge, the actual financial behaviour will be decided by the individual's attitude and personality, which led the proposed model by Yong and Zainal Alam (2021) which identifies two alternative paths to financial literacy. Financial education that forms financial knowledge is sieved through attitude and through the moderating effect of personality, as it is a general understanding that the type of personality determines an individual's behaviour.

2.9 Transtheoretical Model of Behavioural Change (TTM)

The TTM was first posited by Prochaska (1979) to encapsulate the whole chain of changes associated with a person's behaviour. Initially crafted within the psychotherapy field to encapsulate over 300 theories describing behaviour which owes its name, this model's key construct is its intertemporal nature where the process of behaviour change is described in stages. While early in its genesis, the model was used to understand health-related behaviour change. In particular, the behaviour change of individuals towards smoking was understood from the lens of this model, where individuals go through 6 stages from not knowing the benefits of not smoking to overall health all the way to maintaining a healthy lifestyle and no smoking (Prochaska, 1979). However, this model also takes into consideration of relapse, where individuals may regress to old habits and behaviour, post their behavioural change. This model was also applied to a variety of health-related behaviours such as alcohol abuse, drug abuse, high-fat diet and weight control, psychological distress, and sun exposure (Prochaska et al., 1994 as cited in Xiao et al., 2004). The six stages of behaviour change are further understood, with behaviour processes encompassing each stage.

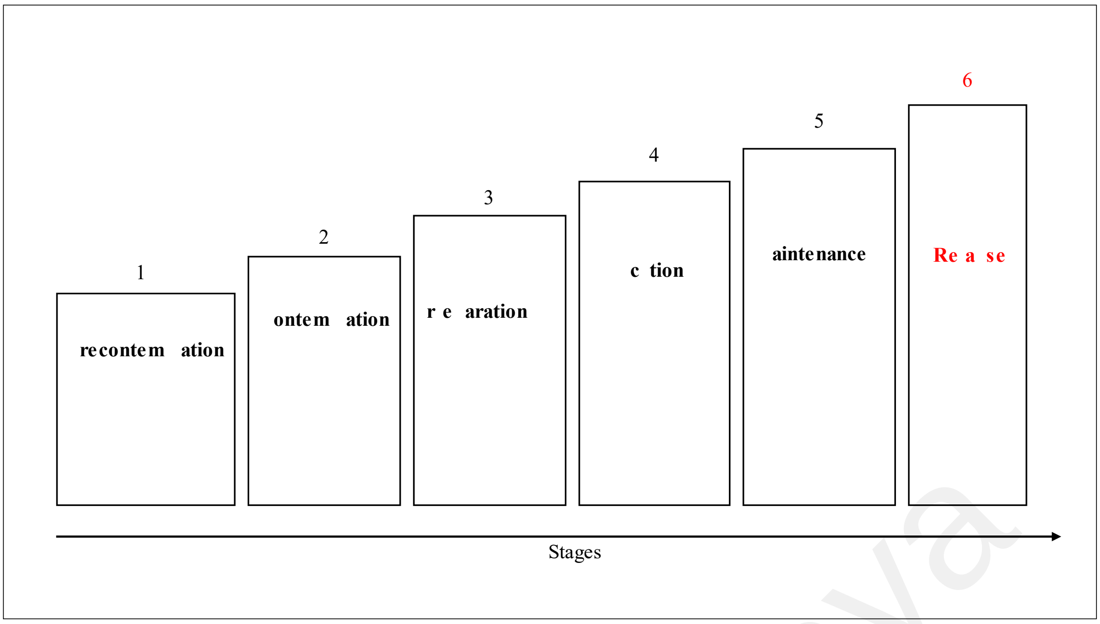


Figure 2.2: 6 Stages of behaviour change

Table 2.5: Change process within TTM

Change Process	Definition	Stages
Experiential		
Consciousness-raising	Discovering and learning new facts, ideas, and strategies to help with healthy behaviour modification.	1
Dramatic relief	Feeling the negative emotions that are associated with risky behaviour.	1
Social liberation	Recognising that social norms are shifting in favour of encouraging healthy behaviour change.	1, 2, 3, 4, 5
Environmental re-evaluation	Recognising the harmful effects of unhealthy behaviour or the beneficial effects of healthy behaviour on one's immediate social and physical environment.	1
Self-re-evaluation	Understanding that changing one's behaviour is a crucial element of one's identity.	2, 3

Table 2.5, continued

Change Process	Definition	Stages
Behavioural		
Self-liberation	Making a clear decision to change.	3, 4

Counter conditioning	Harmful behaviours are swapped with healthy alternative behaviours and cognitions.	4, 5
Stimulus control	Taking away reminders or signals to participate in harmful behaviour and replacing them with clues or reminders to engage in good behaviour.	4, 5
Reinforcement management	Enhancing incentives for good behaviour change while lowering incentives for harmful behaviour.	4, 5
Helping relationships	Seeking and utilising social support for healthy behaviour change.	4, 5

The theory's popularity has grown over the years and has been expanded to explain behaviour change regarding other facets of an individual's life, such as in personal finance and marital relationships (Levesque et al., 2000 as cited in Xiao et al., 2004) and even within organisations (Prochaska, 2000). In essence, this theory successfully captures the totality of the behavioural process chain where change is gradual across time and may even regress. The TTM and the TPB are two theories that have been extensively researched and are widely used in the field of health psychology. The TTM is a model that describes the process of change, while the TPB is a model that predicts behaviour. The TPB is a model that posits that individuals are motivated by three factors — self-interest, social norms, and personal standards. People are likely to behave in accordance with these factors, as they believe that doing so will lead to positive outcomes for themselves (Zainal Alam & Yong, 2021). The TPB predicts that people will behave in accordance with their intended behavioural outcomes. In essence, people will have preconceived notions about what they want to achieve and will make plans to achieve these. The TPB has been found to be particularly useful in predicting people's intentions to change their financial and savings behaviour. While the theory has been found to be effective in predicting people's intentions to change their spending, saving and debt levels, it has not been found to be as effective in predicting people's actual behaviour. This may be due to the complexity of financial and savings behaviour or the fact that people often fail to adhere to their intentions when it comes to money management.

The TTM is a model that posits that behaviour can be changed over time by adopting different stages or models of change. The TTM has four stages: pre-contemplation, contemplation, preparation, and action. In the pre-contemplation stage, individuals are not planning to change their behaviour and may be resistant to change. Pre-contemplation is used interchangeably with pre-intentional motivation while maintenance is used interchangeably with post-intentional volition. In the contemplation stage, individuals are thinking about changing their behaviour but are not committed to doing so. In the preparation stage, individuals are preparing to change their behaviour and may experience some challenges in achieving their goals. In the action stage, individuals implement their changed behaviour. The three components of TPB (i.e. attitude, subjective norm and perceived behavioural control) are underneath a person's intention to change the behaviour of the TTM stage 3 (Boonroungrut & Fei, 2018). The TTM has been found to be applicable to a variety of behaviours, including financial and savings behaviour (Xiao et al., 2004). The TTM has been found to be particularly useful in predicting people's intentions to change their financial and savings behaviour. The TTM model differs from other behaviour change models in the following ways: (a) it incorporates key elements of major psychological theories into a framework to provide more effective interventions; (b) it defines multiple stages of behaviour change, which is different from an action paradigm, and has the potential to reach those who are both ready and unwilling to change the targeted behaviour; (c) it matches intervention strategies to different stages of behaviour change. Finally, it focuses on enhancing self-control which is the key element of the mental accounting theory (Prochaska et al., 1996 as cited in Xiao et al., 2004). In essence, the relationship between the three theories of Mental Accounting theory, TTM and TPB, can be represented below in this study:

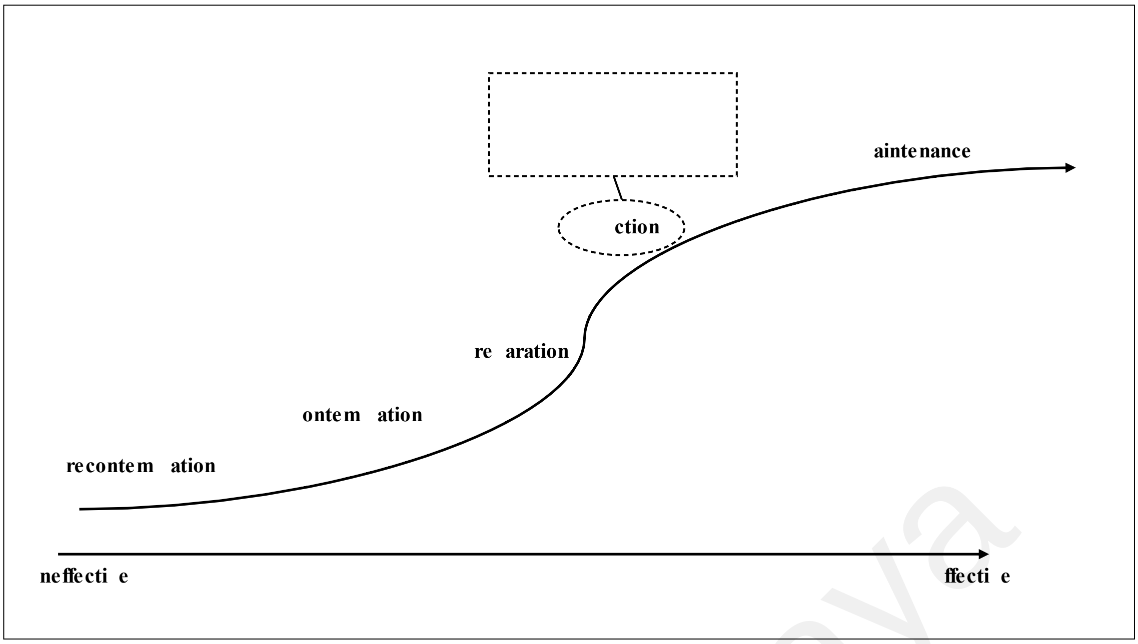


Figure 2.3: Relationship Between the Three Theories of Mental Accounting Theory, TTM and TPB

Table 2.6: Summary of key behavioural concepts and theories

Theory/Model/Concept	Core Construct	Definition	Constraints of Theory
Theory of Reasoned Action (TRA) explains the relationship between attitudes and behaviours, as well as relationships between users of technology and the technology itself.	Attitude toward behaviour Subjective norm	An individual's positive or negative feeling (evaluative effect) about performing the target behaviour. The person's perception is that most people who are important to him think he should or should not perform a behaviour in question.	The theory only applies to behaviour that is consciously thought out beforehand. Irrational decisions, habitual actions, or any behaviour that is not consciously considered cannot be explained by this theory
TPB extends TRA The central factor of TPB is the individual's intention to perform a given behaviour. TPB addresses the issue of behaviours that occur without a person's volitional control.	Attitude toward behaviour Subjective Norm Perceived behavioural control	An individual's positive or negative feeling (evaluative effect) about performing the target behaviour. The person's perception that most people who are important to him think he should or should not perform a behaviour in question. Refers to people's perception of the ease or difficulty of performing the behaviour of interest.	Does not address the variables, such as habit, perceived moral obligation, and self-identity, that may predict intentions and behaviour. Perceived behavioural control not identifying specific factors that might predict behaviour and the biases it may create.
Prospect Theory, also known as the "loss-aversion" theory, explains why individuals try to prevent losses more than they try to make gains	Irrationality in decision making	The prospect theory starts with the concept of loss aversion, an asymmetric form of risk aversion, from the observation that people react differently between potential losses and potential gains. Thus, people make decisions based on the potential gain or losses relative to their specific situation (the reference point) rather than in absolute terms; this	Factors that are equally important to decision-making processes have not been included in the model, such as emotion.

Table 2.6, continued.

Theory/Model/Concept	Core Construct	Definition	Constraints of Theory
		is referred to as reference dependence. Faced with a risky choice leading to gains, individuals are risk-averse, preferring solutions that lead to a lower expected utility but with a higher certainty (concave value function). Faced with a risky choice leading to losses, individuals are risk-seeking, preferring solutions that lead to a lower expected utility as long as it has the potential to avoid losses (convex value function).	
Anchoring explains a cognitive bias whereby an individual's decisions are influenced by a particular reference point or "anchor".	Irrationality in decision making	A cognitive bias refers to the tendency of people to attach or "anchor" their thoughts to one piece of information when deciding, even if this information is an irrelevant or insufficient benchmark.	The concept only applies depending on the size of the anchor, where extreme anchors have limited effect on decision making, and anchoring occurred only if the anchor and preference judgment were expressed on the same scale.
Mental accounting explains individuals' behaviour of categorising and treating money differently depending on where it came from and where it is going.	Cognitive segmentation of resources	This theory posits that individuals divide their wealth and expenses into separate, non-transferable portions. This theory purports that individuals assign different utilities to each category, which affects their consumption behaviour.	Limited generalisability of mental accounts from one individual to another.

Table 2.6, continued.

Theory/Model/Concept	Core Construct	Definition	Constraints of Theory
Confirmation and hindsight bias is a tendency to look out only for information which supports your earlier beliefs or opinions about anything and the belief that you could have predicted an event which happened in the past.	Cognitive processes underlying attitude	Confirmation bias suggests that an individual would be more likely to look for information that supports his or her original ideas about a financial matter than seek out information that contradicts it. Hindsight bias tends to occur in situations where a person believes that the onset of some past event was predictable and completely obvious, whereas, in fact, the event could not have been reasonably predicted. Both biases may result in the oversimplification of matters due to erroneous links made between cause and effect.	-
Hyperbolic discounting theories that a person puts an overly high value on the here and now and an overly low value on the future.	Irrationality in decision making	Refers to the tendency for people to increasingly choose a smaller-sooner reward over a larger-later reward as the delay occurs sooner rather than later in time. When offered a larger reward in exchange for waiting a set amount of time, people act less impulsively (i.e., choose to wait) as the rewards happen further in the future. Put another way, people avoid waiting more as the wait nears the present time.	-

2.10 Analysis Conducted in Studying Retirement Preparedness

Within the social science field, focusing on studies on retirement, it is noted that a vast majority of research used standard statistical analysis to understand the subject of retirement. This fact could be due to the established usage of standard statistical analysis to observe patterns and explain relationships. To the best of the author's knowledge, a non-exhaustive list of studies related to retirement preparedness is provided below, where these studies used standard statistical analysis as a testament to the vast usage and acceptance of the standard statistical analysis methods in this field. However, within the social sciences field focusing on retirement studies, it can be summarised by Garibay et al. (2022) that while machine learning holds some strengths above standard statistics, both methods should be seen as complements rather than substitutes. While reports by industry generally use descriptive analysis or weighted index to determine the level of retirement preparedness of a population, empirical analysis in academia generally uses standard statistical methods to discover and understand the relationship and determinants of retirement preparedness. Of late, while standard statistical analysis remains relevant, the use of its complement, i.e., machine learning, remains limited.

Table 2.7: Standard statistical analysis in study of retirement preparedness

No	Source	Method
1	(Aegon Corporate, 2022, p. 6)	Descriptive analysis
2	(Kim & Hanna, 2015, p. 2)	Logistic regression, Repeated-Imputation Inference (RII)
3	(Lissington et al., 2016, p.11)	Logistic regression
4	(Goldman, 2018, p.10)	Descriptive analysis
5	(Angrisani & Casanova, 2021, p. 5–6)	Probit model marginal effect analysis
6	(Wang et al., 2021, p. 599)	Ordinary Least Squares regression
7	(Ghafoori, 2021, p. 2)	Linear aggregation method
8	(Hasler et al., 2022, p. 4)	Multivariate regression analysis

2.11 Machine Learning for Predictive Analysis

Machine learning can help uncover new insights and understanding of established relationships by identifying complex patterns and interactions in the data, while traditional statistics can provide interpretability and statistical inference. In practice, machine learning is understood as a method that develops algorithms to test models chiefly for the purpose of regression, classification, and clustering of data sets (Athey, 2019). Machine learning can be divided into two branches, i.e., unsupervised and supervised machine learning.

Unsupervised machine learning takes to establishing relationships via clustering. In the field of finance, cluster analysis has been adopted to measure instances of attitudes and behaviour of clients and customers, access to financial services, and stages of development of financial infrastructure across different regions, among others. It is also employed for portfolio optimisation in the space of the capital market. In a study by Fünfgeld and Wang in 2009, a study was conducted using Ward and K-means cluster analysis to categorise individuals based on their demands which include individual attitudes and behaviours in a range of financial matters. The classification of individuals would later be able to be adopted by financial products and service providers to market their services and products, given that the study found that the analysis divided the individuals into five subgroups that define underlying dimensions of financial attitudes and behaviour.

This classification exercise was also carried out in the space of retirement and pension savings. In 2005, Gough and Sozou found that there are six clusters that define the underlying behaviour and attitudes of individuals towards retirement and pension savings. Each cluster had different demographic, economic, behavioural, and attitudinal characteristics. Using the standard form of the statistical package SPSS, the study was carried out using K-means clustering, with six numbers of clusters as the outcome.

Below is a representation of the clustering dendrogram.

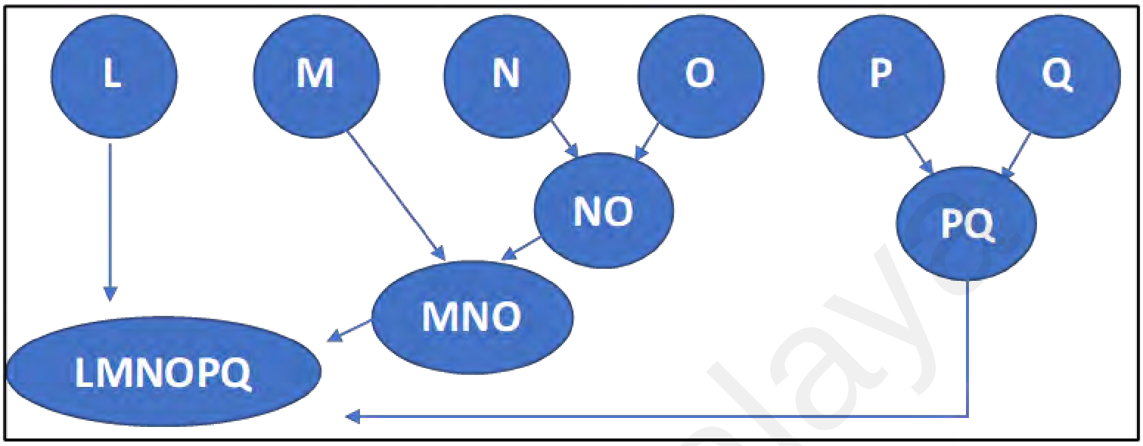


Figure 2.4: Traditional representation of clustering dendrogram

Meanwhile, supervised machine learning typically entails using inputs to predict the output. In predicting the likelihood of an outcome, predictive modelling provides an avenue to predict outcomes given certain inputs. In its basic format, a predictive model could be a simple linear equation. An independent variable is an outcome (features, in machine learning language), whereas the dependent variable (label, in machine learning language) is the input considered to predict the outcome. Predictive modelling can be adopted in forming predictor tools and early warning systems (EWS) (Liz-Domínguez et al., 2019).

To build an accurate predictive model, developers first define the problem and collect data, as data accuracy and volume would produce a more reliable model. For most analytical goals, a combination of clinical data and claims is used (Shugalo, 2020). In machine learning, data is divided into two subgroups where a bigger subgroup is reserved for building the model, and the smaller subgroup is for testing the model's efficiency. The ratio of the data split can range from 80:20, 70:30, and 60:40. To ensure that there is a healthy trade-off between model efficiency and generalisation ability, the study will adopt the 60:40 split, as consistent with Omrani (2015), which saw the usage of the ANN model with 60:40 data split to predict travel mode choice prediction of individuals in Luxembourg providing highest accuracy rate when compared to other machine learning models.

In the field of finance, predictive modelling is widely used especially in relation to fraud detection, managing credit card default risk, and modelling customer lifetime value (Bharadwaj, 2019). In relation to retirement, a deep neural network was developed to determine the optimal consumption utility-based model for retirees who were under defined contribution plans which consider lifetime expected mortality (Chen & Langrené, 2020). The application of machine learning within the financial industry and in social science studies has grown over the years, which can be attributed to the decreasing cost of machine learning software available for researchers. This is seen in the rise of robo-advisors which are taking centre stage in the wealth management space where users receive wealth management service and advice from machine learning-based platforms, thereby cutting cost and time for managing wealth. This enhances accessibility and lowers the barrier to entry into wealth management and the capital market. This comes as an opportune time for the study of retirement preparedness to be conducted using machine learning methods. This will also provide a complement to previous studies from a methodological point of view, as previous studies generally employed econometrics to study retirement preparedness (Crawford & O'Dea, 2020; Herrador-Alcaide et al., 2021; Koh et al., 2021). In this study, a brief illustration below shows the relevancy of using machine learning, where behaviour can be studied using machine learning. Conceptually, studies with theoretical framework that are related to neoclassical economic theory of expected utility and behavioural change can be done via regression, studies with theoretical framework related to action process (process of changing from one behaviour to another) can be conducted via machine learning.

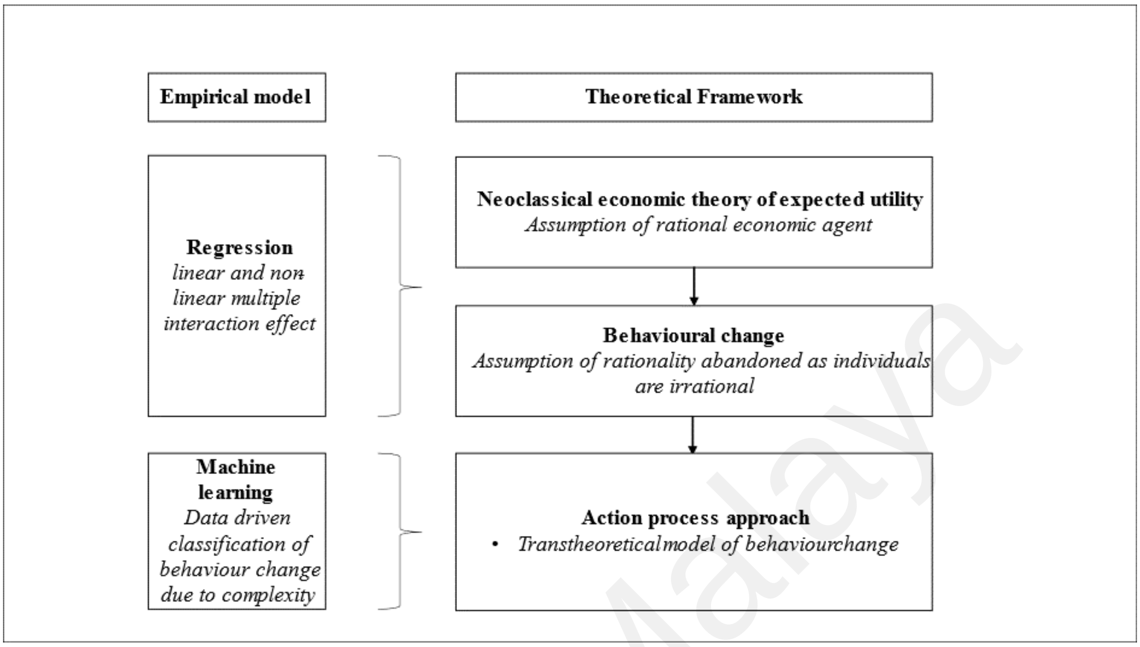


Figure 2.5: Illustration for the relevancy of using machine learning

Other than linear models, there are multiple methods to form predictive modelling or analysis such as Naïve Bayesian classifier, a classifier based on logistic regression, a generalised linear model, Artificial Neural Network (ANN), trees (decision tree, random forest, gradient boosted trees), and numerous algorithms, namely, support vector machines (SVM), k-nearest neighbours (KNN), and random forest (RF). These algorithms allow researchers to reduce errors in designing models to determine relationships between variables, as these algorithms can be analysed systematically and, in a data-driven manner, to be adapted to establish the relationships. In addition, machine learning algorithms typically can learn or adapt in the presence of new data. Such ability allows for the identification of new relationships amidst evolutionary trends.

The algorithms of these supervised machine learning include Naïve Bayesian, Generalised Linear Model (GLM), Logistic Regression, ANN, Decision Tree, Random Forest, and Gradient Boosted Trees, among others.

The model for Naïve Bayesian in this study is defined as below:

$$p\left(\frac{x}{y}=k\right)=\prod_{i=1}^{D} p(x_i|y=k) \tag{1}$$

The generalised linear model (GLM) is shown as below:

$$Y_i = \beta_\circ + \beta_1 X_1 + \varepsilon_i \tag{2}$$

The logistic regression is shown as below:

$$\log\left[\frac{Y}{1-Y}\right] = \beta_\circ + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_n X_n \tag{3}$$

Despite the high level of interpretability for these models and usability for continuous and discrete terms, all three may not be able to model interaction terms and thus might be unsuitable for predicting behaviour. In addition, the simplistic modelling assumptions may lead to underfitting for rich and complex datasets.

Artificial Neural Network (ANN) would be able to provide a succinct prediction towards retirement preparedness and, therefore, is considered for this study's analysis. The model is given by as below:

$$\log\left(\frac{\hat{p}}{1-\hat{p}}\right) = \widehat{m}_{00} + \widehat{m}_{01} \cdot L_1 + \widehat{m}_{02} \cdot L_2 + \widehat{m}_3 \cdot L_3 \tag{4}$$

Despite its low level of interpretability, the ANN is useful for predicting binary outcomes with $\log(\frac{\hat{p}}{1-\hat{p}})$ as the outcome variable, where m is the coefficient while L is the feature. The main neural network regression equation receives the same logit link function featured in logistic regression. As with logistic regression, the weight estimation process changes from least squares to maximum likelihood.

Artificial Neural Network (ANN) is a branch of machine learning which is completely based on neural networks, as neural network mimics the human brain. In this sense, ANN is also a kind of mimic of the human brain in synthesising decisions. ANN has hidden internal workings which may not be readily understood and are prone to overfitting, where it also models the data's errors. In this study, the ANN operator's parameters are two hidden layers, each with 50 neurons constructed. In this regard, a theoretical finding by Lippmann (1987) indicates that an ANN with two hidden layers is appropriate, which is later supported by Madhiarasan (2020) and Ranjan (2022). However, given the limited entry of data that also contains behavioural elements, ANN requires less formal statistical training and can implicitly detect complex nonlinear relationships between dependent and independent variables, if any.

To understand the layers within the neural network, decision trees may be adopted as the algorithm structure of the two models are similar. However, the interpretability levels are different as decision trees have moderate interpretability while ANN has a low level of interpretability. An ensemble of trees in the form of a random forest is also useful where essentially, a random forest enables many weak or weakly-correlated classifiers to form a strong classifier. Visualisations are usually provided for these models as both models do not have a neat and closed functional or equation form.

Gradient boosted trees are also considered for this study, where the model is given by as:

$$F_M(x) = F_0 + v\beta_1 T_1(x) + v\beta_2 T_2(x) + \cdots + v\beta_M T_M(x) \quad (5)$$

where M is the number of iterations. In a similar fashion like ANN, the gradient boosting model is a weighted ($\beta_1 \ldots \beta_M$) linear combination of simple models ($T_1 \ldots T_M$). $F_M(x)$ is, in this case, is the outcome**.** Specifically, the Gradient Boosted Trees model is a forward-learning ensemble method that obtains predictive results through gradually improved estimations.

Support vector machines are not considered in this study despite being available via RapidMiner due to their intensive computational nature and given the possibility of data not being linearly separable. This is as in most financial scenarios; not only is the data not linearly separable, but the hyperplane would make too many mistakes to be a viable solution (SAS Institute, 2020).

There are 15 branches for the Decision Tree model, 20 trees for Gradient Boosted Trees with a depth of 5 branches and 20 trees for Random Forest with a depth of 7 branches. This is the minimum number of branches for the Decision Tree and the optimal number of trees within the Gradient Boosted Trees and Random Forest, as decreasing the number of branches and trees, respectively, would risk lower performance gain. Below is a table that summarises information on each model considered for this study.

Table 2.8: Summary of information on machine learning model

Type of Predictive Modelling	Definition	Application Examples	Advantages	Disadvantages
Naïve Bayesian (NB)	The NB is a classical probabilistic classifier based on Bayes' theorem (i.e. the theory of conditional probability where the likelihood of an outcome occurring is based on a previous outcome occurring). It is used to model linearly separable phenomena. Consider x ϵ X, the input feature vectors; y ϵ {1,…, k}, the class labels; then the NB assumption is: $$p\left(\frac{x}{y}=k\right)=\prod_{i=1}^{D} p(x_i \mid y=k) \quad (6)$$ given by the NB classifier can be trained very efficiently in a supervised learning setting, depending on the precise nature of the probability model. It is viewed as an optimal classifier when there is no dependency between a particular feature and other features, given the class. Although simple, it has proved to be a successful classifier in a wide variety of domains for targets that are binary and nominal with moderate interpretability.	Spam detection, weather forecast, etc.	1. NB is easy to implement over small to large datasets. 2. NB can be trained rapidly. 3. Faster classification process. 4. NB is able to handle huge continuous, and discrete amounts of data. 5. NB is not sensitive to irrelevant features.	1. NB can lead to a loss of accuracy in the result of the analysis. 2. Ignores possible dependencies that might exist in data. 3. Performance of the NB classifier is restricted to situations where the output is categorical. 4. Assumption of linear independence.

Table 2.8, continued

Type of Predictive Modelling	Definition	Application Examples	Advantages	Disadvantages
Generalised linear model (GLM)	The GLM generalises linear regression by allowing the linear model to relate to the response variables through a link function and allows the magnitude of the variance of each measurement to be a function of the predicted value. GLM models are often a "first choice model" that should be compared with complex models carefully, before choosing a complex model to solve problems. Subject to certain conditions met, they have a neat "closed form" solution, which means they can be installed, i.e. trained on the data by simply solving linear algebraic equations. The general equation is shown as below: $$Y_i = \beta_\circ + \beta_1 X_1 + \varepsilon_i \quad (7)$$ The target type for GLM is interval. The model has a high level of interpretability.	Numerous studies across multiple disciplines such as economy, healthcare, and business.	1. GLM can be implemented over small to large datasets. 2. The independent variable can have any form of exponential distribution type. 3. GLM is able to deal with categorical predictors. 4. GLM is relatively easy to interpret and allows a clear understanding of how each of the independent variables influences the dependent variable. 5. GLM is less susceptible to overfitting as compared to linear regression models.	1. GLM requires relatively large datasets, especially with a higher number of independent variables. 2. Users have to manually specify nonlinear and explicit interactions in the model. 3. GLM is sensitive to outliers.

Table 2.8, continued

Type of Predictive Modelling	Definition	Application Examples	Advantages	Disadvantages
Logistic regression	Logistic regression is a tool that allows the investigator to examine the linear relation between a categorical (nominal or binary) dependent variable and a set of continuous and discrete independent variables. Logistic Regression is a special case of Generalised Linear Models where the main benefit of logistic regression over GLM is overfitting avoidance. Therefore, the equation for logistic regression is given as below: $$\log\left[\frac{Y}{1-Y}\right] = \beta_\circ + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_n X_n \quad (8)$$ Logistic regression is essentially a classification algorithm, unlike GLM, that is mainly used for regression purposes. The word "regression" in its name comes from its close sister in the regression domain known as linear regression. Given that the classes are discrete in supervised classification problems, the goal of the algorithms is to find the decision boundaries among the classes. Decision boundaries separate examples of one class from another. The model has a high level of interpretability.	Multiple applications across disciplines in identifying a relationship between independent variables and dependent variables.	1. Logistic regression can be implemented over small to large datasets. 2. Logistic regression is known to be less prone to overfitting. 3. No linear relationship between independent and dependent variables. 4. Predictors are not necessarily normally distributed. 5. Multiple explanatory variables can be used.	1. Logistic regression is unable to predict continuous data as it is built on discrete functions. 2. Logistic regression requires a large set of data to achieve better results. 3. Users must manually specify nonlinear and explicit interactions in the model.

Table 2.8, continued

Type of Predictive Modelling	Definition	Application Examples	Advantages	Disadvantages
	Depending on the problem instance, decision boundaries may be complex and nonlinear in a geometric shape. Logistic regression is known to be less prone to overfitting. On the downside, however, the simplistic modelling assumptions may lead to underfitting for rich and complex datasets.			
Artificial Neural Network (ANN)	ANN is a branch of machine learning which is completely based on neural networks, as neural network mimics the human brain. In this sense, ANN is also a kind of mimic of the human brain in synthesising decisions. It is used to model non-linear phenomena where all interactions considered are fully connected across multiple layers. The outcome variable for this model is usually binary or nominal (categorical).	Image recognition, speech recognition.	1. ANN is suitable for mid-size to large data sets. 2. ANN requires less formal statistical training. 3. ANN can implicitly detect complex nonlinear relationships between dependent and independent variables. 4. ANN can detect all possible interactions between predictor variables.	1. ANN has hidden internal working which may not be readily understood. 2. ANN is prone to overfitting. 3. ANN requires a greater computational burden. 4. ANN model has a low interpretability level.

Table 2.8, continued

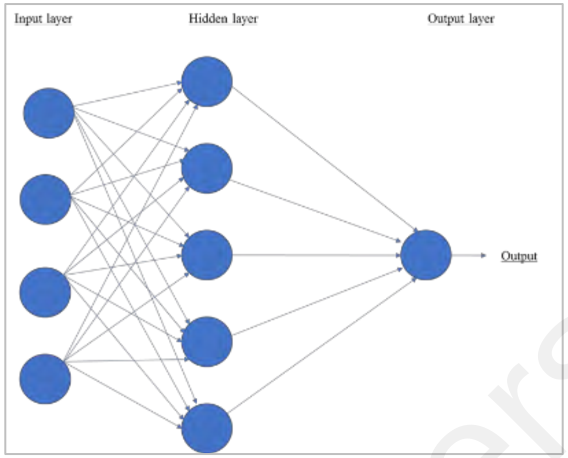
Type of Predictive Modelling	Definition	Application Examples	Advantages	Disadvantages
	 **Figure 2.6:** Novel illustration of neural network The equation for ANN is given as below: $\hat{y} = \hat{m}_{00} + \hat{m}_{01} \cdot L_1 + \hat{m}_{02} \cdot L_2 + \hat{m}_3 \cdot L_3$ (9) Where the predicted variable is influenced by hidden units (L) with its weight estimate (m).			

Table 2.8, continued

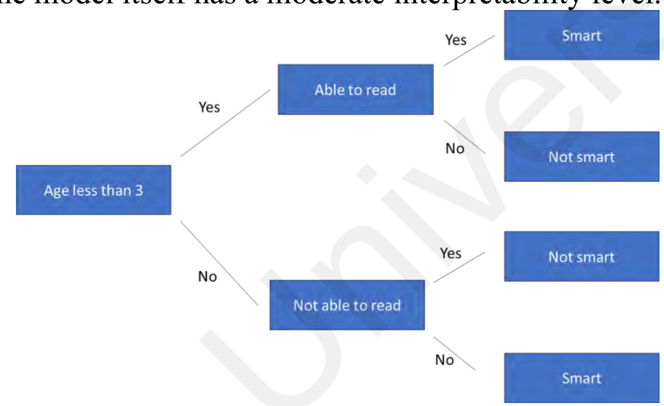
Type of Predictive Modelling	Definition	Application Examples	Advantages	Disadvantages
Decision tree	Decision trees are tree structures that classify instances by sorting them based on feature values. Within a decision tree, a node denotes the selected feature that is used to split input data, and branches denote the values of the node. It is a tree-like model which relates the decisions and their possible consequences. It is used to model non-linear phenomena where interactions are considered implicitly. Missing values and outliers are automatically handled in this model. The consequences may be the outcome of events, cost of resources or utility. The model itself has a moderate interpretability level.  **Figure 2.7:** Novel illustration of decision tree model	Predicting student abnormal behaviour, predicting results.	1. Decision tree model is suitable for mid-size to large data sets. 2. Decision trees can be used for both continuous and discrete attributes. 3. Once the tree is created, it removes unnecessary nodes which do not help in classification resulting in a simpler tree which can be easily interpreted. 4. It is easy to implement. 5. Can work on both continuous and categorical values of output variables.	1. The model is unstable when used with small training sets. 2. It is not suitable for problems where classification is based on the fulfilment of several conditions. 3. If the decision tree consists of too many branches and nodes, the cost and the complexity involved are also very high.

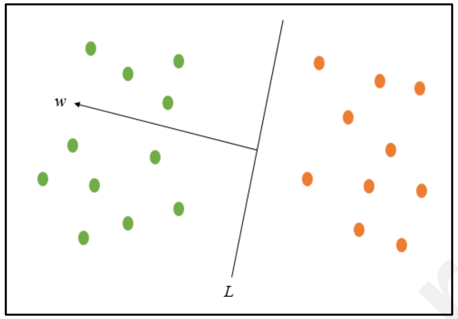
Table 2.8, continued

Type of Predictive Modelling	Definition	Application Examples	Advantages	Disadvantages
Random forest	Random forest is a classifier that evolves from decision trees. It actually consists of many decision trees. To classify a new instance, each decision tree provides a classification for input data; a random forest collects the classifications and chooses the most voted prediction as the result. The input of each tree is sampled data from the original dataset. In addition, a subset of features is randomly selected from the optional features to grow the tree at each node. Each tree is grown without pruning. Essentially, a random forest enables a large number of weak or weakly-correlated classifiers to form a strong classifier. It is used to model non-linear phenomena where interactions are considered implicitly. Missing values and outliers are automatically handled in this model. The model itself has a moderate interpretability level.	Indication of potential customer interest by considering a variety of product characteristics such as colour, size, durability, portability or anything else that customers have indicated an interest in.	1. Random Forest works well with both categorical and continuous variables. 2. Random Forest can automatically handle missing values. 3. Random forest can handle non-linear parameters efficiently.	4. Random forest models have interpretability limitations. 5. For very large data sets, the size of the trees can take up a lot of memory. 6. Random forests tend to overfit.
Gradient boosted trees	A gradient boosted model is an ensemble of either regression or classification tree models. Both are forward-learning ensemble methods that obtain predictive results through gradually improved estimations. Boosting is a flexible nonlinear regression procedure that helps improve the accuracy of trees. By sequentially applying weak classification algorithms to the incrementally changed data, a series of decision trees are created that produce an ensemble of weak prediction	Learning to rank applications	1. Gradient boosted trees model is suitable for mid-size to large data sets. 2. Gradient-boosted trees improve continuously to minimise errors. 3. Gradient-boosted	1. As models improve continuously with new data, it tends to cause overfitting. 2. For very large data sets, the size of the trees can take up a lot of memory because trees are built

Table 2.8, continued

Type of Predictive Modelling	Definition	Application Examples	Advantages	Disadvantages
	models. While boosting trees increases their accuracy, it also decreases speed and human interpretability. The gradient boosting method generalises tree boosting to minimise these issues. It is used to model non-linear phenomena where interactions are considered implicitly. Missing values and outliers are automatically handled in this model. The model itself has a moderate interpretability level. The model is defined as below: $$F_M(x) = F_0 + v\beta_1 T_1(x) + v\beta_2 T_2(x) + \cdots + v\beta_M T_M(x) \quad (10)$$ Where M is the number of iterations. The gradient boosting model is a weighted ($\beta_1 \dots \beta_M$) linear combination of simple models ($T_1 \dots T_M$).		trees work well with both categorical and continuous variables.	sequentially. 3. Gradient-boosted trees are unstable with small training data sets.
Support vector machines (SVM)	Support vector machines are one of the latest models to be developed for pure classification problems. It automatically detects relationships between inputs and outcomes without the user having to specify the relationship prior to designing the model. In its simplest form, it is given by the form below: $$L = \{(w, x0) + b = 0\} \quad (11)$$	Image classification, handwriting recognition, financial decisions, and text mining.	1. SVM can handle small to large datasets.	1. Low interpretability level. 2. In most scenarios, not only is the data not linearly separable, but the hyperplane would make too many mistakes to be a viable solution.

Table 2.8, continued

Type of Predictive Modelling	Definition	Application Examples	Advantages	Disadvantages
	This form can be best explained with the aid of a diagram as below:  **Figure 2.8:** Novel illustration of support vector machines model Where the classification problem is to classify the coloured dots from green and orange. Given the inputs, the SVM is the line (L) that separates the dots perfectly according to their respective colours. w is a perpendicular vector to L. It is the handle that affects the flatness or steepness of the L. x is the vector of predictor variables. b is the bias term, or intercept. It is the measure of the offset of the separating line from the origin. $\langle w, x\rangle$ is the dot product between the vectors w and x.	s		

2.12 Machine Learning in Economic Research

Machine learning has several advantages over econometrics, where for economists, the selection and design of economic and empirical models are largely data-driven. In building a machine learning model, the main goal is to predict, describe, and/or explain some social phenomenon. This signals researchers' main task to identify the model that best accomplishes this goal, under some definition of best where a principle-based, systematic, and strategic approach allows for better performance of models as researchers can fully describe the process of model selection via assessment metrics such as accuracy and error rates (Radford & Joseph, 2020). This leaves a smaller room for the mistake of not including important variables in a model, as empirical models can be compared systematically. Additionally, machine learning can be used to improve the descriptive and predictive power of models, as machine learning models are not limited to linear relationships and can capture non-linear relationships (Radford & Joseph, 2020).

While critics have argued about the interpretability of machine learning models, a key advantage of machine learning is its superior predictive ability. This is because machine learning is better suited to capture interactions across and between variables, regardless of standard econometric constraints related to interaction or compounding effects or multicollinearity (Heo et al., 2020). For studies on behavioural economics, a bottom-up approach (inductive) is encouraged for studies in this field. It departs from traditional economics, which usually employs a top-down (deductive) approach (Davis, 2018)

Regardless, any prediction that may exhibit low interpretability should be theoretically backed to ensure the relevance of the outcomes (Radford & Joseph, 2020). Moreover, by incorporating variables into the model that is relevant according to theory, a model that "fits the data better" and the outputs of the model can then be used to directly test extensions of related theory. The right model, then, is defined by theory (Radford & Joseph, 2020).

Given the proliferation of technology use in social science and economics research (Athey, 2019), much of the machine learning software is now accessible and affordable, which should also be used to complement existing econometrics methods (Charpentier et al., 2018) to enhance understanding of established relationships in the field of economics, especially behavioural economics (Sunstein, 2021). This is further substantiated by Sunstein (2021), where it was argued that once algorithms from machine learning are deployed, it can greatly reduce bias in modelling outcomes of the analysis. When an educator, researcher, financial service professional, lender, or policy maker needs to describe and/or predict a household's future financial situation, it was found that machine learning procedures can provide a robust, efficient, and effective analytic method (Heo et al., 2020). In addition, the complementarity relationship between machine learning and behavioural economics is that behavioural economics provide testable hypotheses which help explain observed patterns of behaviour where machine learning describe patterns in behavioural data (Heal et al, 2022).

Given machine learning's ability to analyse large amounts of data, a machine learning technique will far outperform standard linear econometric models as the size of the dataset increases in tandem with its ability to handle compounding effects of variables when making behavioural predictions and ability to "learn" with the flow of new data (Heo et al., 2020).

Reliance on intuition to make decisions about research design is also minimised and made more systematic with machine learning. For example, when constructing annotation tasks, intuition can lead to overly simplified designs when many other potential approaches could also be equally or more valid (Joseph et al., 2017a as cited in Radford & Joseph, 2020).

In the area of commercial finance, the growth of robo-advisor also signals the growing adoption of artificial intelligence and machine learning which spells its reliability owing to its systematic and robust data-driven processing and delivery of financial advice of clients' information (Hohenberger et al., 2019). Machine learning has also been used in research to describe and predict financial ratios (Sarker, 2021). In relation to financial behaviour, a decision tree analysis was used to understand the determinants of ideal financial behaviours (Lux & Kauzlarich, 2022).

Within the social sciences field focusing on retirement studies, it is summarised by Garibay et al. (2022) that while machine learning holds some strengths above standard statistics, both methods should be seen as complements rather than substitutes.

2.13 Literature Gap

While it is commonly documented that people engage in mental accounting, where wealth and expenses are grouped in distinct categories (Antonides et al., 2011; Hoque, 2017; Huang et al., 2020; Li, 2021), the attempt to study the effect of a formalised structure of mental accounting on retirement preparedness remain limited in Malaysia. While several studies indicate that mental accounting as a self-control and budgeting control may be beneficial to savings behaviour, savings adequacy and retirement preparedness (Antonides et al., 2011; Benz, 2013; Mahapatra & Mishra, 2020; Hoque, 2017), there is a dearth of studies that focus on mental accounting and retirement preparedness despite finding that household do exhibit mental accounting behaviour (Mahapatra & Mishra, 2020). Previous studies looked at savings adequacy for retirement preparedness with the consideration that all categories of wealth and expenditure are fungible and have no differentiation in terms of impact on retirement outcome.

This could be due to the problem of different people having different and unique definitions of “classes” of wealth and expenses, which challenges the attempt to generalise the structure of mental accounting in an individual (Cheema & Soman, 2006). However, this should not be a direct prohibition from pushing towards an incremental understanding of the study of mental accounting towards retirement preparedness as it has been demonstrated in previous studies that individuals in general exhibit structured mental accounting behaviour which features categorisation of wealth into current income, current asset, and future income classes (Mahapatra & Mishra, 2020) where this categorisation also encapsulate the totality of a person’s wealth. It is implied that individuals may also exhibit structured mental accounting behaviour in relation to expenses where expenses are categorised into necessities, discretionary and luxury items (Statman, 2017). As mental accounting disrupts the concept of fungibility of wealth and expenses for an individual, it is expected that these mental accounting categories would have an impact on retirement preparedness. However, the literature remains limited on these categories’ predictive weightage towards retirement preparedness, if at all. Further, the literature remains limited in terms of identifying best mental account allocation recommendations as most studies related to mental accounting were only able to demonstrate the existence of mental accounting behaviour in individuals (Antonides et al., 2011, Mahapatra & Mishra, 2020; Hoque, 2017).

Further, it is also noted that in practice, the estimation of the level of retirement preparedness is generally gauged using built-in calculators that prompt users for personal financial information. These calculators would provide estimations that may be biased and not accurate given the assumptions used, as well as personal financial figures provided by the users themselves, which also may not be accurate. This implies a practical gap, where estimations provided are not based on real-world data and can be taken out of context. It is with limited practicality to provide a figure for a person to save without examining the person's mental accounting behaviour and how it measures against the population's median savings amount as well as the recommended amount of savings.

It is also noted that there is a methodological gap where most studies related to retirement preparedness were done via standard statistics. This methodological gap can be encapsulated in Table 2.7 in section 2.8, where most studies relating to retirement preparedness were done via standard statistical methods.

In line with Garibay et al. (2022), while standard statistical methods and machine learning are complementary, machine learning is preferred when prediction is the aim of the analytical process. In this regard, it is implied that machine learning would be the go-to method in understanding mental accounting towards retirement preparedness.

CHAPTER 3 : METHODOLOGY

3.1 Introduction

In this chapter, the theoretical framework is presented as informed by two overarching behavioural theories, namely, mental accounting theory and the TTM. From these, three hypotheses are formulated, which will be tested in this study. A snapshot of the background of the data as provided by Social Wellbeing Research Centre (SWRC) is included where this dataset is reliable and can be used with ensuing waves of new data for more extensive studies on this topic.

This is then followed by the test and procedure section that explains the analytical method chosen for this study, including the variables adopted in this study.

3.2 Theoretical Framework

The model proposed under the Behavioural Life Cycle builds on the Theory of Interest by Irving Fisher in 1930, where savings is based on five characteristics, i.e., foresight, self-control, habits, expectations of life and adoration of prosperity. The model focuses on foresight as imperative for retirement savings given that it requires long-term planning, self-control as imperative given that immediate consumption is always more tempting than delayed consumption and habits as imperative given that good habits will ensure a healthy level of self-control and successful dealing with problems associated with self-control. The model begins with incorporating self-control which contains elements of temptation, internal conflict and willpower via a dual preference structure that is the doer and the planner.

First, consider an individual whose lifetime extends T periods, with the final period being retirement. The lifetime income stream is given by:

$$Y = Y_1 + Y_2 + Y_3 + \cdots + Y_{T-1} + Y_T \tag{12}$$

For simplicity, this model assumes a perfect capital market with zero real interest rate. Upon retirement, $Y_T = 0$. Lifetime wealth (LW) is given by $LW = \sum_{t=1}^{T} Y_T$ with a consumption stream of:

$$C = C_1 + C_2 + C_3 + \cdots + C_{T-1} + C_T \tag{13}$$

The budget constraint is, therefore, the total consumption being equal to lifetime wealth, i.e., $\sum_{t=1}^{T} C_i = LW$. In the absence of self-control, the optimal savings rate is given by $S_t = Y_t - \left(\frac{1}{T}\right) LW$ where $C_t = \left(\frac{1}{T}\right) LW$. In this model, the conflict associated with self-control is captured by contrasting the time horizon of the doer and the planner, where the doer is assumed to be extremely short-sighted (myopic) and concerned with current consumption only while the planner is focused on maximising lifetime doer utilities. As such, the inclusion of self-control can be described as a deviation from the benchmark lifecycle theory. This is called the planner-doer framework, where an individual is posited to exhibit two sides where the doer is the impulsive side of a person while the planner is the side of a person that is introspective and contemplative. At a particular period, t, the doer's sub-utility is $U_t(C_t)$ is concave in consumption where the doer's marginal propensity to consume is diminishing and the doer faces non-satiation, similar to traditional microeconomics' law of diminishing marginal utility.

Temptation is presented in the model by assuming an opportunity set X_t to represent the feasible choices for consumption at date t. Given no restraint in choosing, the doer will maximise sub-utility by choosing the maximum feasible consumption at period t. Instead, a planner will choose a smaller consumption at period t. This model assumes act of willpower represents a cost which is represented with $W_t(C_t)$. With the inclusion of willpower, the total sub-utility of the doer is now given as the summation of sub-utility

($U_t(C_t)$) and an act of willpower ($W_t(C_t)$) and thereby notated with $Z_t(C_t)$. Therefore, this relationship is given by as below:

$$Z_t(C_t) = U_t(C_t) + W_t(C_t) \tag{14}$$

The doer is assumed to exercise direct control over the consumption choice and, being short-sighted, chooses C_t that can maximise $Z_t(C_t)$ on the set of opportunities X_t. This choice is the combined influence of both planner and the doer. Willpower be effective only when $Z_t(C_t) \neq U_t(C_t)$ and $W_t(C_t) \neq 0$.

Given willpower can be applied in varying degrees (from completely giving in to the temptation to completely not giving in to temptation), the definition of willpower effort variable is denoted as θ_t, which is the degree of willpower effort needed to induce the individual to select a consumption level C_t in the face of the opportunity set X_t.

This model first assumes that an increase in willpower θ_t reduces consumption C_t such that $\frac{\partial \theta_t}{\partial C_t} < 0$. Secondly, this will also lead to a reduction in total doer sub utility $Z_t(C_t)$ such that an increase in θ will change $Z_t(C_t)$ negatively where $\frac{\partial Z_t}{\partial \theta_t} < 0$. Therefore, $\frac{\partial Z_t}{\partial \theta_t} \times \frac{\partial \theta_t}{\partial C_t} > 0$.

Thirdly, increasing willpower effort becomes more painful (disutility) when additional willpower is applied. Consumption then will be reduced in the face of additional willpower applied where $\frac{\partial \left[\frac{\partial Z_t}{\partial \theta_t} \times \frac{\partial \theta_t}{\partial C_t}\right]}{\partial C_t} < 0$.

Lastly, willpower effort becomes less costly towards retirement where $\frac{\partial Z_t}{\partial \theta_t} \times \frac{\partial \theta_t}{\partial C_t}$ decreases at a constant rate in t.

To represent the planner, which is the rational counterpart of an individual's personality, the model associates the neo-classical utility function $V(\cdot)$ to the planner, where it forms the sub utility Z_1 to Z_T. Since $\frac{\partial Z_t}{\partial \theta_t} < 0$, willpower costs are automatically incorporated within the planner's choice problem. Given willpower is costly, a planner will seek other means to reduce willpower costs and achieve self-control.

One alternative to willpower is the restriction of the future opportunity set X_t. This can be done by imposing a constraint mechanism, such as putting funds in a pension plan that reduces disposable income and restricts withdrawals. Such a mechanism is known as a rule. For example, the planner chooses a rule that commits future consumption to a particular path. The doer, by the time of the future, would then have no need to exercise willpower. In essence, a planner will choose consumption that maximises the planner's utility at $\theta = 0$ and the mechanism that enables this is known as an external rule. Optimal consumption at this point is denoted by C^* where it forms the first best solution to the planner's problem and fits perfectly to the life cycle consumption path (consumption smoothing).

Therefore, it can be implied that the traditional Life Cycle Hypothesis is a special case of the Behavioural Life Cycle, i.e., when willpower effort, $\theta = 0$ and the first best rule is available to the planner. However, zero willpower effort rarely happens as there is a limited number of pension plans and investments in these funds rarely determine the consumption path. Moreover, uncertainty about income flow and spending needs makes pension plans impractical. Where $\theta \neq 0$, the mechanism that is put in place by the planner to determine the path of consumption is known as the internal rule.

Therefore, it can be derived from here that utility loss when willpower is used is more than the marginal utility decrease attributable to less consumption.

$$D = \left[\frac{\partial Z_t}{\partial \theta_t} \times \frac{\partial \theta_t}{\partial C_t}\right] - \frac{\partial Z_t}{\partial C_t} > 0 \tag{15}$$

D simply decreases when consumption increases and, conversely, will reach zero when consumption reaches infinity. In essence, D is the net marginal cost of using willpower. However, Ainslie (1975) suggests that there are limits on the type of rules in keeping willpower costs low. These include habitual rules that should be simple, as complex rules would require conscious thinking while habits are subconsciously complied with. Exceptions made to the rules must be rare and well-defined to avoid conscious thinking as well. Rules must be dynamic and stable, as habits are not easily changed.

To indicate how different willpower effort costs for the three mental accounts' balances can be included in the model, the theory focuses first on the current income, where it postulates that the higher the temptation, the higher the willpower cost required to choose a certain consumption level that is lower than the current income account balance (denoted as M_t). At any $C_t < M_t$, the increased temptation will make the doer worse off, as presented below:

$$\frac{\partial Z_t}{\partial M_t} = \frac{\partial W_t}{\partial M_t} + \left(\frac{\partial W_t}{\partial \theta_t} \times \frac{\partial \theta_t^*}{\partial M_t}\right) > 0 \tag{16}$$

And

$$\frac{\partial \left[\frac{\partial Z_t}{\partial \theta_t} \times \frac{\partial \theta_t}{\partial C_t}\right]}{\partial M_t} < 0 \tag{17}$$

which entails a person who will face a higher temptation to spend a sum of money given a higher salary. For instance, a person with a monthly salary of RM4,000 will require higher willpower to spend just RM200 rather than a person whose monthly salary is RM1,200 (which means the more a person has, the more tempting it is to consume more). The theory also postulates that within the current income account, the intention to consume the same amount of money in successive increments produces less negative impact. For example, given spending of RM200, the impact of temptation on an additional amount of salary of RM1,000 (from RM4,000 to RM5,000) involves less willpower than effort than the RM1,000 increase from RM1,200 to RM2,200. This means the same amount to spend presents different temptation levels for a different increase in wealth and income levels. In addition, gains and losses are also viewed differently according to prospect theory developed under mental accounting theory. In particular, an individual is assumed to integrate multiple losses while segregating multiple gains. When a larger gain is faced with a smaller loss, the two are integrated, while when a larger loss is faced with a smaller gain, the two are segregated. The objective of this division is to maximise psychological pleasure and minimise pain. For example, faced with the choice of 100% of winning RM50 with a 50% chance of winning RM100, humans will always be loss averse and choose the first choice despite the probabilistic outcome of the two options being the same. This behaviour is consistent with the mental mechanism of viewing types of wealth and expenditure differently.

This study aims to explore presence of mental accounting behaviour in individuals, to examine the predictive power of mental accounting attributes on retirement satisfaction, and finally, to compare pre-retirees' retirement thinking, and retirees' retirement satisfaction in terms of mental accounting attributes predictive power. In this regard, it is hypothesised that mental accounting behaviour is present in retirement satisfaction where gains and losses are viewed differently; mental accounting attributes do have predictive power on retirement satisfaction, and better mental accounting allocation can enhance retirement preparedness as a better mental accounting allocation can lead to retirement satisfaction.

Separately put, the achievement of retirement preparedness which is indicative of retirement satisfaction for those who have retired (i.e., current retirees), can be indicated by maximised utility, Zt(Ct). Maximising of utility is, therefore, when an individual changes their mental accounting behaviour from untrained mental accounting behaviour to best mental accounting behaviour as informed by the TTM. In this regard, retirement outcome relates to the satisfaction level a person achieves in retirement. In essence, maximum utility (i.e., retirement satisfaction) can be achieved subject to the ability to change to (or acquire) best behaviour of allocation of wealth into theorised mental accounting category. In this case, it is represented as a single-product utility maximisation problem where the single product is the best mental accounting allocation. The utility maximisation problem of the individual can be expressed as follows:

$$\max Z_t(C_t)\ s.t.\ \sum_{t=1}^{T} C_t = I + A + F = W(MA) \tag{18}$$

where W(MA) is wealth allocated by mental accounting behaviour. The expression above explains that maximising utility (i.e. achieving retirement preparedness) is subject to total consumption being equivalent to wealth as per best mental accounting behaviour and allocation. Here, in a similar fashion to traditional microeconomics' law of diminishing marginal utility, marginal propensity to consume is diminishing and the individual faces non-satiation. Therefore, $\frac{\partial Z_t}{\partial C_t} > 0$ where maximum utility is satisfaction in retirement, as evident in best mental accounting behaviour.

For this study's analysis, the allocation of wealth and expenses in categories as informed by mental accounting theory (current income, current wealth, future income, necessary items, discretionary items, and luxury items) is investigated for retirees who report satisfaction in retirement, and this will be taken as the standard benchmark for best mental accounting allocation since it is posited that best mental accounting wealth allocation could bring about retirement satisfaction. For example, if it is found that for individuals (who report as being prepared for retirement, i.e., satisfied in retirement), wealth, in general, is ranked in terms of predictive power, such as in future income first, and then current asset and finally current income while also for expenses, ranked in terms of predictive power such as in luxury items least, followed by discretionary items and necessary items, then this will be considered as the best mental accounting allocation or behaviour in this study. Working regressively, this benchmark will then be taken as the benchmark for achieving retirement satisfaction.

Subsequently, the study can also be represented in Figure 3.1. The figure below shows how best mental accounting allocation is achieved in a single wealth category through behaviour change. For example, best mental accounting allocation for an individual is achieved by the individual prioritising consumption of the best single wealth category first before moving into the second wealth category. As the Transtheoretical Model of Behaviour Change (TTM) is leveraged upon in this study, it is conceptually mooted that the best mental accounting allocation is a behaviour that is encouraged, hence, a person would move from the first stage of the TTM (not knowing what is the best mental accounting allocation) towards the last stage of the TTM (exhibiting the best mental accounting allocation). When moving from the first stage to the last stage of TTM, a person is conceptually mooted to gain utility (satisfaction) in retirement outcome.

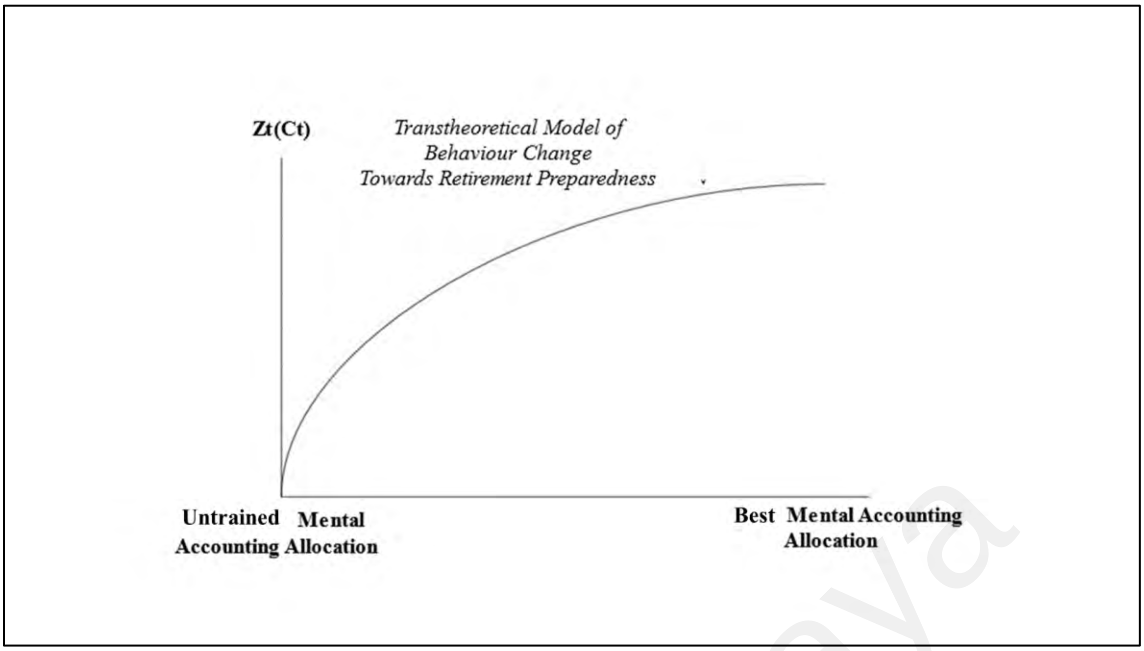


Figure 3.1: Illustration of theoretical framework

Here, it is proposed that the influence factor for retirement preparedness based on mental accounting (i.e., wealth and expenditure allocation decision) towards achieving best satisfaction in retirement can be explained in the following. Firstly, consider,

$$I_d = \gamma + \alpha J_A + \beta K + \varepsilon \tag{19}$$

Where I_d represents the outcome for retirement, J_A represents the allocation of wealth and expenditure in mental accounting categories (here, assumed as one variable), and K represents the individual's characteristics. In this case, let $I_d < 1$ be the condition when the desired level of satisfaction is not achieved, while $I_d \geq 1$ be the condition when the desired level of satisfaction is achieved. Therefore, when the desired level of satisfaction is not achieved,

$$\gamma + \alpha J_A + \beta K + \varepsilon < 1 \tag{20}$$

$$\varepsilon < 1 - \gamma + \alpha J_A + \beta K$$

$$\varepsilon < 1 - E(I_d)$$

$$\Pr[\varepsilon < 1 - E(I_d)] = \emptyset\,[1 - E(I_d)] \tag{21}$$

Here, for the sake of explanation, consider the error term distribution following the Gaussian distribution. Similarly, if the desired level of satisfaction is achieved,

$$\gamma + \alpha J_A + \beta K + \varepsilon \geq 1 \tag{22}$$

$$\varepsilon \geq 1 - \gamma + \alpha J_A + \beta K$$

$$\varepsilon \geq 1 - E(I_d)$$

$$\Pr[\varepsilon \geq 1 - E(I_d)] = \emptyset\,[1 - E(I_d)] \tag{23}$$

Now, consider a two-period timeline where the expected outcome for retirement at period 1 is given by:

$$E(I_d^t) = \gamma + \alpha(1 - \tau^t) + \beta K^t \tag{24}$$

While at period 2, the expected outcome for retirement is given by:

$$E(I_d^{t+1}) = \gamma + \alpha(1 - \tau^{t+1}) + \beta K^{t+1} \tag{25}$$

Where τ is disposable income after allocation of wealth in mental accounting categories (i.e., 1 - J_A). Meanwhile, consider that individual characteristics in the second period, K^{t+1} is a function of individual characteristics in the first period, K^t and ω is the magnitude of the difference in disposable income after the allocation of wealth in mental accounting categories, where ω is the wealth coefficient, such that:

$$K^{t+1} = K^t + 1^t\omega\,(\tau^t - \tau^{t+1}) \tag{26}$$

This equation can then be substituted back into the equation for the expected outcome for retirement at period 2, such that:

$$E(I_d^{t+1}) = \gamma + \alpha(1 - \tau^{t+1}) + \beta[K^t + 1^t\omega\,(\tau^t - \tau^{t+1})] \tag{27}$$

From there, the change of outcome for retirement can be derived by subtracting the expected outcome for retirement at period 1 equation with the equation 27, such that:

$$E(I_d^{t+1}) - E(I_d^t) = (\gamma + \alpha(1-\tau^{t+1}) + \beta[K^t + 1^t\omega\,(\tau^t - \tau^{t+1})]) - \gamma + \alpha(1 - \tau^t) + \beta K^t \tag{28}$$

$$\Delta(I_d) = (\gamma - \gamma) + (\alpha(1-\tau^{t+1}) - \alpha(1-\tau^t)) + (\beta[K^t + 1^t\omega\,(\tau^t - \tau^{t+1})] - \beta K^t)$$

$$\Delta(I_d) = [\alpha - \alpha\tau^{t+1} - \alpha + \alpha\tau^t] + [\beta K^t + \beta^t\omega\tau^t - \beta^t\omega\tau^{t+1} - \beta K^t]$$

$$\Delta(I_d) = [-\alpha\tau^{t+1} + \alpha\tau^t] + [\beta^t\omega\tau^t - \beta^t\omega\tau^{t+1}]$$

$$\Delta(I_d) = [\alpha\tau^t - \alpha\tau^{t+1}] + [\beta^t\omega\tau^t - \beta^t\omega\tau^{t+1}]$$

$$\Delta(I_d) = \alpha[\tau^t - \tau^{t+1}] + \beta^t\omega[\tau^t - \tau^{t+1}]$$

$$\Delta(I_d) = (\alpha + \beta^t\omega)(\tau^t - \tau^{t+1}) \tag{29}$$

Therefore, it is the inference here that the change in retirement outcome level over time is dependent on the magnitude of α and β, i.e., the magnitude of allocation of wealth and expenditure within mental accounting categories and the magnitude of the difference of disposable income after allocation of wealth in mental accounting categories and magnitude of individual characteristics. In this study, retirement preparedness is defined as the best mental accounting strategy a person should have that can lead to retirement satisfaction. Should a person have an optimised allocation of wealth and expenditure according to mental accounting categories, then he or she is prepared for retirement. If not, the person would be better off re-arranging their mental account allocations to ensure that he is on track and better prepared toward achieving retirement satisfaction. Disposable income has been demonstrated in studies to influence retirement preparedness (Lusardi, 2007). However, this study suggest that it is a function of mental accounting behaviour where mental accounting behaviour influences the relationship between disposable income and retirement outcome (i.e, level of retirement satisfaction a person achieves).

3.2.1 Mental Accounting Assumption

The usage of savings behaviour and adequacy to explore existence of mental accounting behaviour is as individuals have been demonstrated in past studies to exhibit mental accounting behaviour in non-monetary terms (Huang et al., 2020; Kahneman & Tversky, 1979; Shefrin & Thaler, 1988; Townsend, 2018; Yeh, 2020). This study assumes that having or not having good savings behaviour and/or adequacy when coupled with tendency of thinking in retirement for pre-retirees and satisfaction in retirement for retirees can imply behaviour of different valuation between gains and losses. With objective elements combined with subjective elements to imply behaviour is consistent with Noone et al. (2013). Separately, mental accounting involves splitting wealth into three categories, i.e., current income, current assets, and future income. They are presented as below; note that s represents savings, Y_t represents wealth, C_t represents expenditure or consumption, and LW represents life time wealth:

Table 3.1: Mental accounting for wealth

Current income, I **(Most tempted to use for current consumption)**	$\boldsymbol{I = (1 - s)Y_t}$
Current asset, A	$A = \sum_{t=1}^{T}[(1 - s)Y_t - C_t]$
Future income, F **(Least tempted to use for current consumption)**	sLW

To present the mental accounting structure, an illustration of the total doer's sub utility Z_t against consumption C_t is given by as below:

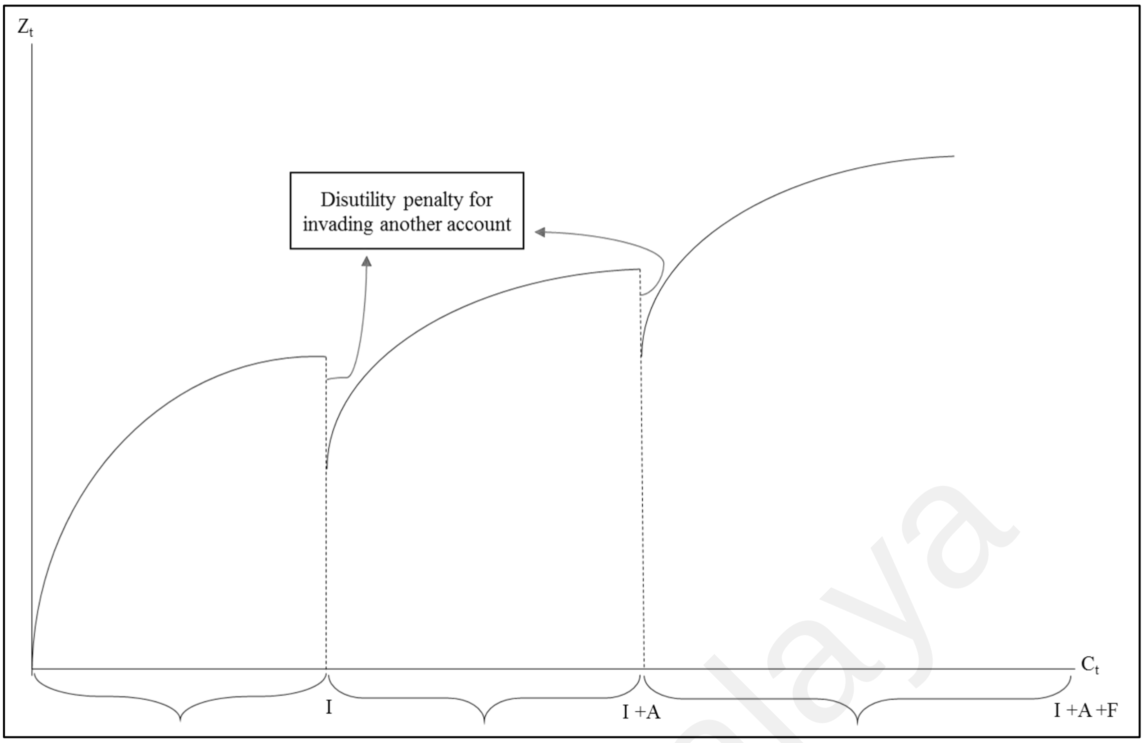


Figure 3.2: Concave utility for mental accounting

As consumption increases, utility increases at a diminishing rate. This, in turn, also means that willpower decreases. Once the balance in the current income account is depleted, there will be no requirement for willpower to be exerted on this account. The following marginal consumption is funded out of the next account, i.e., the current asset account. Using the balance in the current asset account, A is less tempting than using the balance in the current income account, I, consumption of A, presents a cost or a penalty in terms of disutility. The same explanation applies when the balance in A is depleted, and the individual invades the final account, future income account, F. The key postulate of the theory is the non-fungibility of wealth, and the marginal propensity to consume is dependent on the type of account. Where utility functions are concerned, the theory suggest that utility function for each mental accounting category is different which ensures its applicability after considering behavioural biases such as mental accounting behaviour.

3.2.2 Transtheoretical model of behaviour change (TTM) in Retirement Preparedness

In this theory, it is posited that an individual goes through six stages towards complete behaviour change. In essence, this theory captures the journey an individual goes through in forming new habits and also the possibility of relapsing to old behaviours. It was first formulated to describe changes an individual goes through in forming new healthy habits. The stages in this theory that relates to behaviour towards retirement preparedness can be defined in such a way that in the precontemplation stage, an individual may not be aware that they are not capable of planning towards retirement preparedness, where they may not effectively allocate, save, and spend their wealth. Through interventions in the contemplation stage, they may have intentions to prepare themselves to be fit for retirement by thinking about how to save better via best mental account allocation. In the preparation stage, individuals begin to plan to take the initiative to be prepared for retirement by following through with learning how to save better for retirement. Following this, a person may see that his attitudes towards being prepared for retirement begin to change for the better; subjective norms skew towards being satisfied with retirement life and that the individual perceives that they are capable of living in retirement, satisfied. This is where the action happens, where the individual makes deliberate changes in lifestyle to be prepared for retirement by actually allocating their wealth and spending more wisely. Finally, it only takes maintenance of this behaviour to lead to being prepared for retirement. In this study, the tendency of a respondent to think about retirement represents a person's inner thoughts of planning for retirement. Retirement satisfaction is defined as the level of life satisfaction a respondent achieves in retirement. As the Transtheoretical Model of Behaviour Change (TTM) is leveraged upon in this study, it is conceptually mooted that the best mental accounting allocation is a behaviour that is encouraged, hence, a person would move from the first stage of the TTM (not knowing what is the best mental accounting allocation) towards the last stage of the TTM (exhibiting the best mental accounting allocation). When moving from the first stage to the last stage of TTM, a person is conceptually mooted to gain utility (satisfaction) in retirement outcome.

3.2.3 Hypothesis Development

Stemming from mental accounting in individuals where wealth and expenditure categories are broken down into separate non-fungible categories, it is hypothesised that these wealth and expenditure categories significantly influence overall retirement preparedness. This is because it has been demonstrated that wealth and expenditure do influence retirement preparedness (Brounen et al., 2016; Dynan et al., 2004). Naturally, such a hypothesis becomes relevant and testable in the face of these findings. In this regard, the mental accounting construct for the wealth and expenditure component is solidified into current income, current asset, and future income categories for wealth (Shefrin & Thaler, 1988), as well as necessity, discretionary, and luxury items for expenditure categories (Statman, 2017). The non-fungible categorisation of wealth and expenditure is conceptually mooted to have implication on retirement outcome (Garnick, 2017; Statman, 2017) which provides the justification for this study. Demographic variables are also included to test the relationship between an individual's demographic factors to retirement satisfaction, where satisfaction is used as an aim towards becoming prepared for retirement, given its relevance in previous studies (Brounen et al., 2016; Mustapha & Jeyaram, 2015). The empirical method is a scientific research method used to investigate and measure the effects of independent and dependent variables on a given phenomenon. It relies on the collection and analysis of data through observation and experimentation. The empirical method is often used to test hypotheses in the social and behavioural sciences.

The empirical method begins with the formulation of a question or hypothesis to be investigated. This question or hypothesis is then tested through the collection and analysis of data. The data is collected through the use of observation or experimentation. In this regard, the study is linked to the theoretical framework via the hypothesis below:

Hypothesis 1: Mental accounting behaviour is present in individuals, where gains and losses are viewed differently.

Hypothesis 2: Mental accounting attributes have predictive power on retirement satisfaction.

Hypothesis 3: Re-arrangement of allocation between pre-retirees' retirement thinking, and retirees' retirement satisfaction in terms of mental accounting attributes will lead to increase retirement preparedness among individuals.

3.3 Data Source

The study is undertaken via primary data from the first wave of the MARS survey conducted in the year 2018 by the Social Wellbeing Research Centre (SWRC) at the Faculty of Economics and Administration of University of Malaya[2]. While MARS survey itself is designed to be a longitudinal survey, this study only uses only the first wave of the survey data, hence, rendering the study to be using cross-sectional data. In particular, rather than focusing on a particular trend via longitudinal study, the study opts a cross-sectional data which when analysed with ANN, is sufficient in capturing behavioural elements exhibited by respondents. In this regard, it is unlikely that the study's outcome

[2] MARS data is under the ownership of Social Wellbeing Centre of University of Malaya and its access can only be provided via an official application to the data holders at http://swrc.um.edu.my/research/mars/

can determine the trend of behaviour throughout time. As Malaysians come from various economic backgrounds, this study intends to use the first wave of the Malaysian Ageing and Retirement Survey (MARS) conducted in 2018, capturing the information needed for this study. The survey was collected from Malaysians across a broad spectrum of socio-economic and demographic backgrounds such as age, gender, income, consumption, state, etc. The usage of MARS data is due to a lowered risk of data collection errors. The survey is a Computer-Assisted Personal Interviews (CAPI) survey where data collection was done in a transparent manner. The collection of data processed by trained individuals is recorded for audit purposes.

Conducted in collaboration with the Department of Statistics Malaysia, the survey is designed to be representative of the Malaysian population and is comparable with similar surveys in various countries across the world, such as the United States Health and Retirement Survey (HRS), Japanese Study on Aging and Retirement (JSTAR), and Aging and Retirement in Europe (SHARE). The sampling methodology is a multiple-stage sampling framework where each region is stratified by urban and rural areas called enumeration blocks (EBs) which are proportionate to the population size of each region (Mansor et al., 2019). As the population in Kuala Lumpur is lower than compared to Sabah, Perak, Johor, Kedah, Sarawak, Kelantan, Selangor, Terengganu, and Pahang. With reference to 2018 DOSM population census for ages 40 years old and above, MARS survey is on proportionate allocation to the population size of the states. A further re-sratification for gender and ethnic component was conducted to ensure that sample data remain representative of the population.

The questions in the survey range from topics relating to family support and living arrangement to health, healthcare utilisation, psycho-social and cognition, income and consumption, housing and assets, work, employment, and retirement. For this study, aspects of health, health utilisation, psycho-social and cognition are not focused on. The benefit of using MARS data is that future studies can be built upon this study, where an exploration of the behaviour of respondents is collected across many years. In this regard, it is nearly impossible to conduct a separate survey to collect behavioural information on the same set of respondents.

This study focused on individual Malaysians, where as many as 5,613 interviews[3] were completed across 3,384 households. However, a total of 3,067 responses were used from the MARS wave 1 survey data from a total number of 5,613 respondents. The reduction in number was due to the 2,546 respondents who did not either answer or report their views on retirement (i.e. questions pertaining to how often they think about retirement for those who have yet to retire and questions on life satisfaction in retirement for those who have retired). In this study, all pre-retirees are defined as aged less than 60 years old are working either formally or informally. For retirees as they are above 60 years old, they no longer work post-retirement. The breakdown of the demographics of all the respondents of the MARS Wave 1 2018 is as shown in Table 3.2. Further discussion on the breakdown data is presented on Chapter 4, section 4.2 Descriptive Analysis of Demographics.

The age of respondents collected was 40 years old and above. This comes as those below the age of 40 generally do not save at all and are found to be in financial distress. Many spend beyond their means and struggle to pay off their debts (Asian Institute of Finance [AIF], 2015; ICMR, 2021) and including younger respondents would risk skewing the results of the data analysis. While the MARS survey targeted households, the information collected was on an individual basis. Should there be more than one

[3] One response was initially omitted due to lack of reporting consistency which brings the total response rate to 5,612 responses.

eligible member in a selected household, a maximum of three oldest eligible members would be selected as possible respondents (Mansor et al., 2019).

Table 3.2: Demographic Breakdown of MARS WAVE 1 2018 Data

Demographic Factors	Frequency (n=5,612)	Percent (%)
Gender		
Female	3,132	56%
Male	2,480	44%
Ethnic		
Bumiputera	4,377	78%
Chinese	622	11%
Indian	452	8%
Others	161	3%
Marital Status		
Married	4,353	78%
Single	1,259	22%
Education		
No schooling	674	12%
Primary school	1,612	29%
Secondary School	3,058	54%
Tertiary	268	5%
Employment Status		
Retired	1,069	19%
Unemployed	2,367	42%
Working now	2,176	39%
Number of Dependents		
1 to 5	4,434	79%
6 to 10	1,093	19%
11 and above	85	2%

For this study, data from several items pertaining to demographics, income, expenditure, and savings are used.

- A101RSex pertains to gender (1 for Male; 5 for Female; DK for Don't Know, RF for Refused)
- A101RDOB prompts respondents for date of birth which can be used to determine as person's age as at year 2018 (DD/MM/YYYY)
- A202 pertains to ethnicity (1. Malay; 2. Chinese; 3. Indian; 97. Others)
- A204 pertains to marital status (1. Never married; 2. Married; 3. Widowed – since what year: _____________; 4. Divorced/ Separated – since what year: ______________; DK Don't Know; RF Refused)
- A205 pertains to highest level of education.
- A101 pertains to number of dependents.
- E102 and E103 Type of income
- E107 Type of expenditure
- F104a Type of Savings
- Section B1: Family Support and Transfer – Children
- Section B2: : Family Support and Transfer – Parents

3.4 Empirical Model

For exploring the existence of mental accounting in respondents, the study focused on current retirees' saving behaviour, savings adequacy, and the level of satisfaction they reported. In essence, the study intends to go in depth via descriptive analysis with these respondents by comparing their savings behaviour and savings adequacy to their reported retirement satisfaction. Similarly, the study also looked at pre-retirees savings behaviour, savings adequacy and the tendency of them thinking about retirement. The usage of savings behaviour and adequacy to explore existence of mental accounting behaviour is as individuals have been demonstrated in past studies to exhibit mental accounting behaviour in non-monetary terms (Huang et al., 2020; Kahneman & Tversky, 1979; Shefrin & Thaler, 1988; Townsend, 2018; Yeh, 2020). This study assumes that having or not having good savings behaviour and/or adequacy when coupled with tendency of thinking in retirement for pre-retirees and satisfaction in retirement for retirees can imply behaviour of different valuation between gains and losses. With objective elements combined with subjective elements to imply behaviour is consistent with Noone et al. (2013). This method is conducted to detect any evidence of mental accounting behaviour, in terms of the respondents' prospects, where it is posited that individuals' gains and losses are also viewed differently according to mental accounting theory. An individual is assumed to integrate multiple losses while segregating multiple gains. When a larger gain is faced with a smaller loss, the two are integrated, while when a larger loss is faced with a smaller gain, the two are segregated. The objective of this division is to maximise psychological pleasure and minimise pain.

For examining the mental accounting attributes predictive power on retirement satisfaction, the machine learning method is used where the independent variables are known as features, and the dependent variable is known as a label; the terms "independent variables" refer to the mental accounting categories of wealth, mental accounting categories of expenditure, and demographic variables as well as "dependent variable" to refer to the binary outcome of retirement satisfaction (e.g., yes or no to being satisfied in retirement) is maintained for clarity of language.

The empirical model for predicting retirement satisfaction is given as below:

$$
\begin{aligned}
&p(retirement\ satisfaction) \\
&\qquad = \beta_{\circ} + \beta_1(current\ income) + \beta_2(current\ asset) \\
&\qquad + \beta_3(future\ income) + \beta_4(necessities) \\
&\qquad + \beta_5(discretionary\ items) + \beta_6(luxury\ items) + \beta_7(age) \\
&\qquad + \beta_8(gender) + \beta_9(ethnic) + \beta_{10}(education) \\
&\qquad + \beta_{11}(marital\ status) + \beta_{12}(household\ size)
\end{aligned}
$$

The empirical model for retirement satisfaction identifies the best mental accounting allocation as this can bring satisfaction in retirement which is the target in retirement while the empirical model for thinking about retirement identifies the mental accounting allocation by pre-retirees in the thinking about retirement stage. Towards being prepared for retirement, the comparison of mental accounting categories ranking is conducted to identify the gap between ranking in best mental accounting allocation and mental accounting allocation by pre-retirees in the thinking about retirement stage. This feeds into the theoretical framework which suggests utility should increase (towards achieving satisfaction in retirement) as a person moves from untrained mental accounting behaviour to best mental accounting behaviour. This spells out that as a person moves from untrained mental accounting allocation to best mental accounting allocation, he/she will be more prepared for retirement.

In the third objective, which is to compare pre-retirees' retirement thinking, and retirees' retirement satisfaction in terms of mental accounting attributes predictive power, the study will focus on both pre-retirees and current retirees' mental accounting categories of wealth, mental accounting categories of expenditure, and demographic variables. The empirical model for predicting tendency of thinking about retirement is given as below:

$$
\begin{aligned}
&p(tendency\ of\ thinking\ about\ retirement) \\
&\qquad = \beta_{\circ} + \beta_1(current\ income) + \beta_2(current\ asset) \\
&\qquad + \beta_3(future\ income) + \beta_4(necessities) \\
&\qquad + \beta_5(discretionary\ items) + \beta_6(luxury\ items) + \beta_7(age) \\
&\qquad + \beta_8(gender) + \beta_9(ethnic) + \beta_{10}(education) \\
&\qquad + \beta_{11}(marital\ status) + \beta_{12}(household\ size)
\end{aligned}
$$

Consistent with Zainal Alam et al. (2022), it must be noted that the expression for the model above is not the actual functional form; rather, it is a novel interpretation of "p(retirement satisfaction)" and "p(tendency of thinking about retirement)". As such, these terms are merely the factors in the model and do not reflect the real structure of the model. Supervised machine learning in the form of predictive modelling is used for predictive analysis.

For the second and final objective, the study focused on mental accounting categories of wealth, mental accounting categories of expenditure, and demographic variables. It is also worth noting that for this study, 60% of the data is used for training the algorithms, while another 40% is used for testing the algorithms in forming reliable models. The data split is consistent with previous studies that used the same ratio in predicting behaviour (Omrani, 2015). The validation in the model is a multi-hold out set validation. The model will be trained on 60% data, and the 40% test data will be divided into seven subsets. Once the model is trained, it will be used to make predictions on each of the seven subsets independently, and the performance of these seven subsets will be averaged. The multi-hold-out method is good to use when starting to build an initial model in a data science project. The performance of the models is based on the test data set.

3.4.1 Artificial Neural Network (ANN)

Based on the literature review, Artificial Neural Network (ANN) would be able to provide a succinct prediction of retirement satisfaction and the tendency to think about retirement, and therefore, is considered for this study's analysis. ANN model typically does not make any prior assumptions about data distribution before learning. This greatly promotes the usability of ANNs in various applications (Yang & Yang, 2014).

Despite its low level of interpretability, the ANN is useful for predicting binary outcomes with $\log(\frac{\hat{p}}{1-\hat{p}})$ as the outcome variable (retirement satisfaction & tendency of thinking about retirement). The main neural network regression equation receives the same logit link function featured in logistic regression. As with logistic regression, the weight estimation process changes from least squares to maximum likelihood. Artificial Neural Network (ANN) is a branch of machine learning which is completely based on neural networks, as neural network mimics the human brain. In this sense, ANN is also a kind of mimic of the human brain in synthesising decisions. Further the motivation for this study stems from the machine learning definition of "let the machine learn a model with a training dataset and test the model in the other test dataset". This study concerns behavioural economics, where a bottom-up approach (inductive) is encouraged for studies in this field. It departs from traditional economics, which usually employs a top-down (deductive) approach (Davis, 2018).

ANN has hidden internal workings which may not be readily understood and is prone to overfitting, where it also models the data's errors. In this study, the ANN operator's parameters are two hidden layers, each with 50 neurons constructed. In this regard, a theoretical finding by Lippmann (1987), Ranjan (2022), and Madhiarasan (2020) indicated that an ANN with two hidden layers with 50 neurons is appropriate. However, given the limited entry of data that also contains behavioural elements, ANN requires less formal statistical training and can implicitly detect complex nonlinear relationships between dependent and independent variables.

The structure of the ANN can be presented as below:

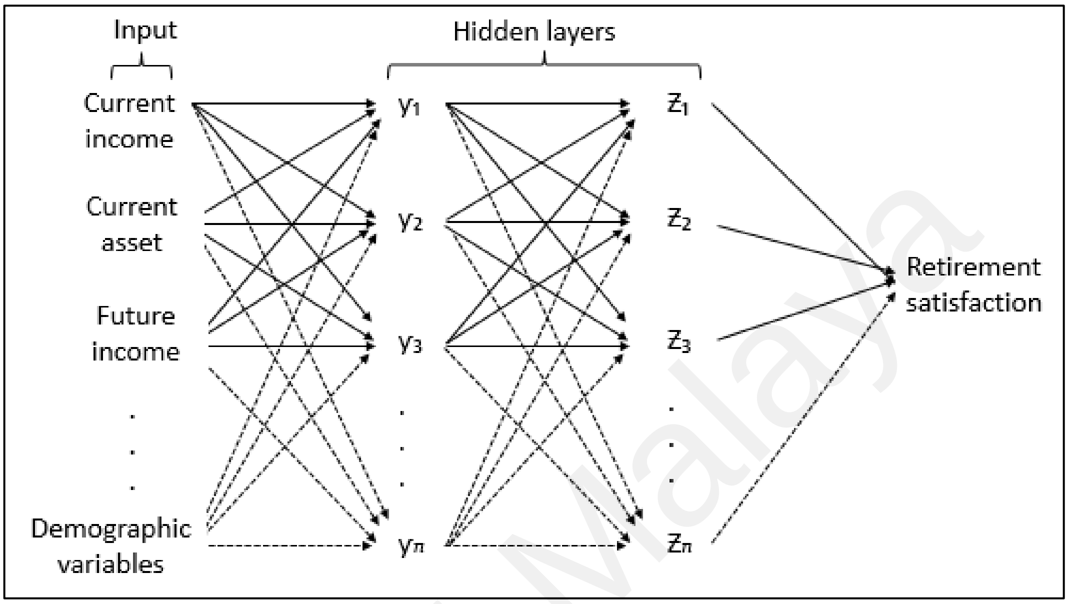


Figure 3.3: Novel illustration of structure of ANN

To understand the mechanism of ANN, which is made up of a number of neurons, a discussion on the mathematics behind a single neuron is considered. Firstly, consider the illustration below:

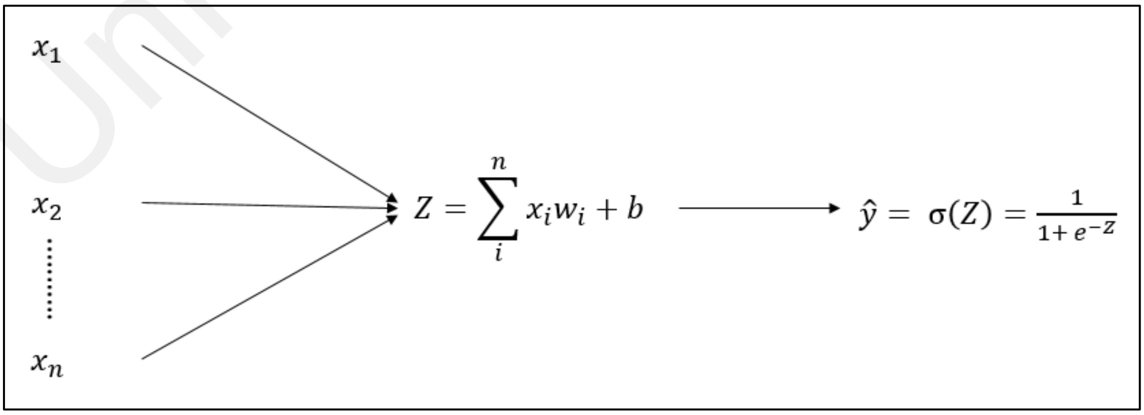


Figure 3.4: Novel illustration of a single neuron

In this illustration, n number of inputs, x_i (otherwise known as features, or independent variable) with respective weights, w_i and bias, b, is passed to one hidden layer, Z such that it is equal to $\sum_{i=1}^{n} x_i w_i + b$. Bias, which is also known as the offset, is necessary in most cases to move the entire activation function to the left or right to generate the required output values. Through an activation function, Z is passed to the output of the neuron. Given that this study employs a binary categorical target variable, the discussion will use the logistic function (sigmoid curve) as the activation function, denoted as $\hat{y} = \sigma(Z) = \frac{1}{(1+e^{-Z})}$.

A learning algorithm such as a single neuron is made up of two parts, i.e., backpropagation and optimisation. In the backpropagation part, the pertinent question is to know exactly how far the predicted value is from the actual value of the target, otherwise known as the loss function. In general, a mean square error is used, where:

$$MSE = (actual\ value - predicted\ value)^2 \qquad (30)$$
$$= (y_i - \hat{y}_i)^2$$

This is then done for all data in the training set and averaged thereafter. The consolidation is the cost function. The cost function is, therefore, the average of loss functions.

$$C = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (31)$$

From the cost function, it is pertinent to know how the cost function changes with respect to weights and bias. This is to identify what weights and bias that can best minimise the errors to achieve an accurate model. Therefore, the change of the cost function with respect to weights is mathematically presented as below:

$$\frac{\partial C}{\partial w_i} = \frac{\partial C}{\partial \hat{y}_i} \times \frac{\partial \hat{y}_i}{\partial Z} \times \frac{\partial Z}{\partial w_i} \quad (32)$$

Where:

a) $\frac{\partial C}{\partial \hat{y}_i} = \frac{2}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)$;

b) $\frac{\partial \hat{y}_i}{\partial Z} = \frac{\partial \sigma(Z)}{\partial Z} = \frac{\partial}{\partial Z}(\frac{1}{1+e^{-Z}}) = \frac{e^{-Z}}{(1+e^{-Z})^2} = \left(\frac{1}{1+e^{-Z}}\right) \times \frac{e^{-Z}}{1+e^{-Z}} = \left(\frac{1}{1+e^{-Z}}\right) \times \left(1 - \left(\frac{1}{1+e^{-Z}}\right)\right) = \sigma(Z) \times \left(1 - \sigma(Z)\right)$; and

c) $\frac{\partial Z}{\partial w_i} = \frac{\partial \sum_{i=1}^{n}(x_i \cdot w_i + b)}{\partial w_i} = x_i$

Therefore,

$$\frac{\partial C}{\partial w_i} = [\frac{2}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)] \times \left[\sigma(Z) \times \left(1 - \sigma(Z)\right)\right] \times x_i \quad (33)$$

Meanwhile, the change of the cost function with respect to bias is mathematically presented as below:

$$\frac{\partial C}{\partial b} = \frac{\partial C}{\partial \hat{y}_i} \times \frac{\partial \hat{y}_i}{\partial Z} \times \frac{\partial Z}{\partial b} \quad (34)$$

Here, it is assumed that bias is to the power of 1, i.e., b^1. Therefore,

$$\frac{\partial C}{\partial b} = [\frac{2}{n}\sum_{i=1}^{n}(\hat{y}_i - y_i)] \times \left[\sigma(Z) \times \left(1 - \sigma(Z)\right)\right] \quad (35)$$

In the optimisation part, the selection of the best weights and biases is done where α, a hyperparameter, is used to control how much weights and biases are changed. Mathematically, it is presented as below:

$$w_{i_{new}} = w_{i_{old}} - (\alpha \times \frac{\partial C}{\partial w_i}) \quad (36)$$

$$b_{i_{new}} = b_{i_{old}} - (\alpha \times \frac{\partial C}{\partial b}) \quad (37)$$

The feed-forward Neural Network uses the supervised Back Propagation (NNBP) algorithm for training. The connections between the nodes do not form a directed cycle. Information only flows forward from the input nodes to the output nodes through the hidden nodes. Settings in RapidMiner included two hidden layers for the network. The momentum simply adds a fraction of the previous weight update to the current one, which prevents local maxima and smoothens optimisation directions.

To understand the layers within the neural network, decision trees may be adopted as the algorithm structure of the two models are similar. However, the interpretability levels are different as decision trees have moderate interpretability while ANN has a low level of interpretability. However, the predictive performance of the model remains the key focus of this study.

In this study, the RapidMiner Studio (RapidMiner) version 9.9 Education Edition software is used for the purpose of data analysis (Mierswa & Klinkenberg, 2018). Developed in 2001 by Ralf Klinkenberg, Ingo Mierswa, and Simon Fischer, this software was suitable for analysis. Its simple yet powerful algorithms can detect multidimensional and non-linear relationships that may exhibit. Additionally, the analysis process is understandable for non-data scientists, which allows for replication of this study in different settings as it contains more than 100 learning schemes for classification, regression, and clustering tasks (Lanio, 2021).

The flow modelling will be as below:

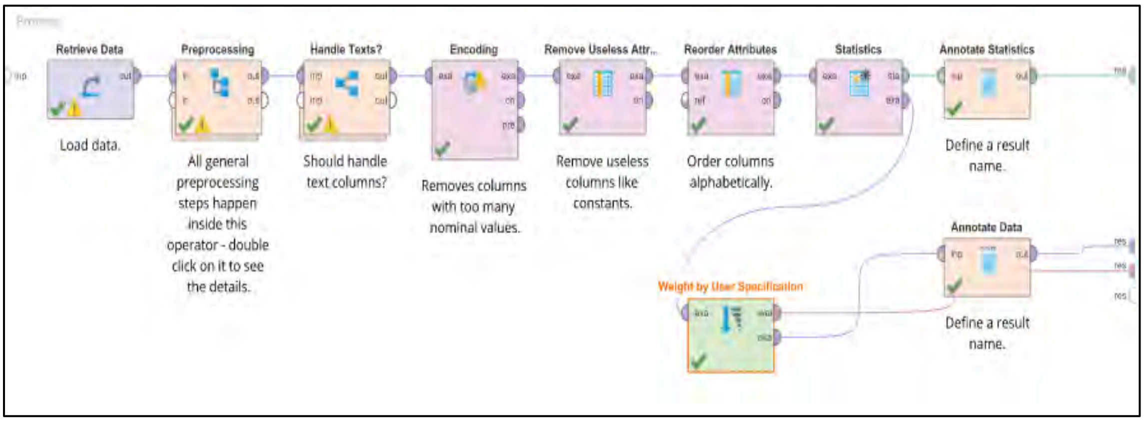


Figure 3.5: Modelling flow chart

For the purpose of this study, a further seven assessment metrics are introduced to assess the ANN model used. For evaluation metrics accuracy, precision, recall, F measure, and specificity, a reading of more than 50% is considered acceptable. For classification error, a reading of less than 50% is acceptable, while AUC will be assessed by comparing ROC curves of all algorithms where the algorithm with the biggest area under the curve is judged the best performing model for this evaluation metric. The seven-assessment metrics are as below:

Table 3.3: Assessment metric information

No.	Assessment Metric	Details
1	Accuracy	Accuracy of the model is considered in assessing the performance of the model, where accuracy forms the proportion of correctly classified data (true positive and true negative) over all data that was used in validation.
2	Classification error	Classification error is the opposite of accuracy, where it is the proportion of incorrectly classified data. A better model would have a lower reading of classification error.
3	Area under Receiver Operating Curve (ROC) (AUC)	ROC, which stands for receiver operating characteristics curve, is a graph that plots the true positive rate (proportion of correctly classified positive data by an algorithm) against the false positive rate (proportion of incorrectly classified positive data by an algorithm). Mathematically, true positive rate (otherwise known as recall or sensitivity) is presented as below: $$True\ positive\ rate = \frac{True\ Positive}{True\ Positive + False\ Negative}$$ While false positive rate is mathematically presented as below: $$False\ positive\ rate = \frac{False\ Positive}{False\ Positive + True\ Negative}$$ The ROC curve shows the performance of a model at all classification thresholds. The area under the ROC curve (AUC) measures the aggregate measure of performance across all possible classification thresholds. A bigger AUC value would suggest a better model, given that the area shows the probability of correct predictions made by the model.
4	Precision	Precision is defined as the proportion of positive classification made by the model that was correct over all that was identified as positive data. Mathematically, it is presented as below: $$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}$$ Precision is the ability of the model to predict correctly. A higher precision would direct to a better model.
5	Recall (also known as sensitivity)	A higher value of recall would point to a better model, as higher recall would refer to higher correctly identified positives. Basically, recall is the ratio of correctly identified positives over all true positives.

Table 3.3, continued.

No.	Assessment Metric	Details
6	F Measure	F measure is a harmonic mean of recall and precision. An F measure would refer to how precise as well as how robust the model is. A higher F measure would mean a better predictive power of a model.
7	Specificity	Specificity is the rate of correctly classified negatives in the data by a model. Mathematically is presented as below: $$True\ Negative\ rate = \frac{True\ Negative}{True\ Negative + False\ Positive}$$ A higher value of specificity would refer to a model that has a high ability to correctly identify false values.

True positive: Correctly identified true data. For instance, the model correctly predicted retirement satisfaction or often thinking about retirement with the inputs in the model.

True negative: Correctly identified false data. For instance, the model correctly predicted lack of retirement satisfaction or not often thinking about retirement with the inputs in the model.

False positive: Incorrectly identified true data. For instance, the model incorrectly predicted retirement satisfaction or often thinking about retirement with the inputs in the model.

False negative: Incorrectly identified false data. For instance, the model incorrectly predicted lack of retirement satisfaction or not often thinking about retirement with the inputs in the model.

In addition to the performance metrics used to assess the ANN model, the discussion on the performance of other machine learning models discussed in section 2.11 Machine Learning for Predictive Analysis as well as its attributes predictive powers will also be conducted. To further enrich the discussion on the methodology, the ANN model will also be compared against a logistic regression model as a baseline standard statistical analysis model.

3.4.2 Test & Procedure

3.4.2.1 Dependent variable

For this study, items were separated based on retirement status, i.e., before retirement and currently retired. It is represented in Table 3.4 and Table 3.5:

Table 3.4: Combination for descriptive analysis for presence of mental accounting behaviour in pre-retirees

Savings behaviour ***(Objective element of retirement preparedness)***	**Savings adequacy** ***(Objective element of retirement preparedness)***	**How often have you thought about retirement?** ***(Subjective element of retirement preparedness)***
YES	YES	OFTEN
YES	YES	NOT OFTEN
YES	NO	OFTEN
YES	NO	NOT OFTEN
NO	YES	OFTEN
NO	YES	NOT OFTEN
NO	NO	OFTEN
NO	NO	NOT OFTEN

Table 3.5: Combination for descriptive analysis for presence of mental accounting behaviour in retirees

Savings behaviour ***(Objective element of retirement preparedness)***	**Savings adequacy** ***(Objective element of retirement preparedness)***	**Are you satisfied with your retirement?** ***(Subjective element of retirement preparedness)***	**What would you say about your retirement life compared to before retirement?** ***(Subjective element of retirement preparedness)***
YES	YES	YES	GOOD
YES	YES	YES	NOT GOOD
YES	YES	NO	GOOD
YES	YES	NO	NOT GOOD
YES	NO	YES	GOOD
YES	NO	YES	NOT GOOD
YES	NO	NO	GOOD
YES	NO	NO	NOT GOOD
NO	YES	YES	GOOD
NO	YES	YES	NOT GOOD
NO	YES	NO	GOOD
NO	YES	NO	NOT GOOD
NO	NO	YES	GOOD
NO	NO	YES	NOT GOOD
NO	NO	NO	GOOD
NO	NO	NO	NOT GOOD

Under the MARS survey questionnaire, two questions were posed to current retirees that deal with satisfaction in retirement. Here, the current retirees are 60 years old and above and no longer work. In one, respondents were asked if they were satisfied with their retirement (binary, coded "yes" and "no"):

Item D134 Overall, are you satisfied with your retirement? (Answers: 1. Very Satisfied [" "]; 2. [" "]; . [" "] .

Meanwhile in another, respondents were asked to compare the life before retirement to life in retirement (binary, coded "good" and "not good"):

Item D135 Comparing before and after retirement, what would you say about your life after retirement? (Answers: 1. Better than before [" "]; 2. About [" "]; . W [" "] .

In this study, the second question is used for the second objective analysis as the responses given in relation to life before retirement and after retirement, which is more relevant to this study, given that it captures a more nuanced view of satisfaction in retirement.

Separately, item D123 "How often have you thought about retirement?" (Answers: 1. A lot [coded as "Often"]; 2. Some [coded as "Often"]; 3. A little [coded as "Not often"]; 4. Hardly at all [coded as "Not often"]) were asked of respondents who are yet to retire. Here, the preretirees are below 60 years old and still work. While this is the sole question that captures pre-retirees subjective thoughts on retirement, it is important, given that it alludes to a person's intention of planning for retirement, which is a key determinant towards being better prepared for retirement (Adams & Rau, 2011; Barnes & Parry, 2004; Curl & Ingram, 2013; Davis, 2007; Hewitt et al., 2010; Reitzes & Mutran, 2004; Topa et al., 2009, as cited in Principi et al., 2018) while questions "Are you satisfied with your retirement?" (coded as "yes" and "no") and "What would you say about your retirement life compared to before retirement?" (coded as "good" and "not good") sheds light on the psychological fitness in retirement for those who have retired. These questions are in line with previous studies and are coded to be binary (Noone et al. 2013; Palací et al., 2018).

8) The dependent variable retirement satisfaction corresponds to the second objective. Further, this dependent variable together with the tendency of thinking about retirement variable is used for objective 3. In this regard, retirement satisfaction relates to retirement life satisfaction compared to life prior to retirement. Tendency of thinking about retirement relates to how often a person thinks about retirement. These dependent variables are related to mental accounting as mental accounting is conceptually seen to impact retirement behaviour and outcome.

For savings behaviour item which is binary (yes or no to saving) is approximated via the difference of annual income to annual expenses where if the difference is positive, savings is assumed to have occurred and would be coded as "yes", while if the difference is negative or zero, savings is assumed to not have occurred and would be coded as "no". This step is taken as respondents prefer not to disclose their savings behaviour, and the closest approximate to detecting an incidence of savings is via any disposable income after respondents have spent on all personal expenditure items for a particular year. While the survey does include the question of whether the respondents do have savings, it does not indicate the savings behaviour of the respondents due to the wording of the survey, as respondents may or may not be aware of their own savings and that the current savings could have been given to them from other parties such as their parents or employers.

For the savings adequacy item, EPF's recommended amount was found to be more suitable for the research objective to gauge savings adequacy for retirement as the amount needed in retirement life can be approximated with the amount needed by an elderly couple. This also comes at a time when most of Malaysia's population is in urban areas.

In this regard, the minimum total amount to sustain consumption in retirement is RM37,080 multiplied by years remaining from retirement at age 60 (or current age for current retirees) to 99 years old with an assumed discount rate of 3%. The assumed discount rate is from the average discount rate in Malaysia[4]. The assumed discount rate is from the round off of average inflation rate in Malaysia. This rate is taken from the average inflation rate in Malaysia from 1987 to 2021, with projections up to 2027 as take from the World Economic Outlook Database October 2022. The age of 99 years old was chosen given that the probability of death at this age is near 1 (World Health Organisation, 2020). This presents a conservative view of savings considering the expectation of longevity, whereas if a person lives longer, they may need to save more to sustain their consumption. Mathematically it is represented as below:

$$Total\ wealth\ at\ retirement$$
$$= \begin{cases} (Total\ Current\ Asset + Total\ Future\ Income) \times (1 + 3\%)^{60-age} & if\ age\ < 60 \\ Total\ Annual\ Current\ Income + Total\ Asset + Total\ Future\ Income & if\ age\ \geq 60 \end{cases}$$

The total wealth in retirement would then be compared with the total minimum recommended amount of consumption in retirement. Mathematically, it can be represented as below, which was derived from the formula for the present value of an annuity:

[4] https://www.statista.com/statistics/319033/inflation-rate-in-malaysia/

$$Total\ consumption\ in\ retirement$$

$$= \begin{cases} RM37{,}080 \times \left(\dfrac{1 - \dfrac{1}{(1+3\%)^{99-60}}}{3\%} \right) \times \left(\dfrac{1}{(1+3\%)^{60-age}} \right) & if\ age < 60 \\ RM37{,}080 \times \left(\dfrac{1 - \dfrac{1}{(1+3\%)^{99-age}}}{3\%} \right) & if\ age \geq 60 \end{cases}$$

Should total wealth exceed or be equal to the needed amount to sustain retirement consumption, the person is considered to have adequate savings amount. This forms a binary item where a person may have adequate retirement savings amount (coded as "yes") and may not have adequate retirement savings amount (coded as "no"). Savings behaviour and savings adequacy form the objective element in the descriptive analysis for the presence of mental accounting behaviour in respondents.

The distinction between the subjective questions asked to pre-retirees and current retirees is as the experiences between these two cohorts about retirement are different, as well as for the purpose of comparative analysis between the two cohorts, and thus calls for a separate treatment between the two groups.

3.4.2.2 Independent variables

For the purpose of analysis with respect to mental accounting, current income includes the sum of pension, rental income, salary/income from the business, insurance, allowances from Social Security Organisation (SOCSO), Social Welfare Department (Elderly/Disability aid), Zakat/donation received, dividend from shares or unit trusts, subsidies/cost of living allowance (Bantuan Sara Hidup), allowance or contribution from Armed Forces Fund Board (LTAT), net intergenerational transfers and others combined in Ringgit Malaysia.

Current assets refer to the sum of home equity, land, other properties, shares of the business, insurance, bank savings (fixed deposit, savings/current account and others combined in Ringgit Malaysia. While future income refers to the sum of Employees Provident Fund (EPF) savings etc.), properties, Tabung Haji (Islamic Pilgrimage Fund), Unit trust/ASNB/endowment, shares, private retirement schemes and others combined in Ringgit Malaysia. These mirror the items within the wealth categories as in Schooley and Worden (2008).

Similarly, due to the presence of mental accounting, for this analysis, the expenditure component is also segmented into three segments, i.e., necessity items, discretionary items and luxury items ascending utility level. As opposed to the wealth component, this segmentation of expenditure is used as utility to spend for the next segment once the current segment is exhausted, increases.

Necessities refer to the sum of costs for transportation (petrol, touch 'n' go, public transport, parking, school van, etc.), electricity, water, Indah Water fee (fee for national wastewater and sanitation company), and food combined in Ringgit Malaysia. Following Statman (2017), food type is not differentiated and is assumed to fall within the necessary consumption category. Within the MARS survey questionnaire, an item (item E107) was included where respondents would self-report their average monthly expenditure. In this item, food consists of eating out/groceries/household needs (e.g., detergent, floor cleaner, garbage bags, etc. The self-reported value was used for the purpose of this study's analysis. Discretionary items refer to the cost of telephone/mobile phone/prepaid, toiletries, house repairs and others combined in Ringgit Malaysia. Luxury items refer to costs for internet, Astro/Netflix/TV Box, payment for domestic services, newspapers/magazines, membership fees and others in Ringgit Malaysia. These mirror the items within the expenditure categories as in Statman (2017). The data for these independent variables (i.e., different classes of wealth and consumption types) were coded in nominal Ringgit value.

As the final component in the analysis relating to the first objective of this research, demography would include age (ranging from 40 years old to beyond 80 years old), gender (male or female), ethnicity (Bumiputera, Chinese, Indians, or others), education (no schooling, primary school, secondary school, or tertiary education), marital status (single or married) and household size. The data for independent demographic variables were coded as per indicated categories, given that the chosen software can capture labels for categorical variables as it is. The analysis considers respondents of age 40 and above as, according to the Life Cycle hypothesis, this is the age where income peaks and, thus, would be most suitable to analyse their savings behaviour. It is also found that those below the age of 40 generally struggle to save for retirement as they might not find saving for retirement to be a top priority; seeming that other financial obligations such as mortgages and car loans would come first (ICMR, 2021; MFPC, 2018; Noone et al., 2010). Gender is also included in the analysis to investigate whether gender plays a role in towards retirement preparedness. These demographic factors were deemed important for this study as the same demographic factors were chosen in previous studies related to this study (Zainal Alam et al, 2022).

CHAPTER 4 : RESULTS AND DISCUSSION

4.1 Introduction

In this chapter, the characteristics of the respondents are first presented for clarity before delving into the results of the tests. This is mainly to understand the limitations of the data and to be able to draw certain conclusions for this study. Once the characteristics of the respondents are discussed, discussions on the presence of mental accounting are presented. In section 4.2, the results of the presence of mental accounting behaviour in respondents are discussed. This is followed by section 4.3, where the results of the predictive power of mental accounting allocation on retirement satisfaction are presented. Thirdly, results for comparison of pre-retirees' retirement thinking, and retirees' retirement satisfaction in terms of mental accounting allocation predictive power are provided as well in section 4.3. In this regard, these sections will be the answers to this study's research questions on the retirement preparedness of Malaysians with respect to behavioural economics considerations. In addition, the results of evidence of the influence of demographic factors on retirement preparedness are also presented in this chapter. Lastly, a discussion on how to further improve the current retirement preparedness is presented in this chapter. This study is conducted with three objectives. The summary of the objectives is to utilise predictive modelling for pursuing retirement preparedness of Malaysians with a focus on mental accounting, where wealth and expenditure are divided into three non-fungible categories each, and gains and loss are viewed differently.

It is pertinent to understand relevant predictors towards retirement preparedness. This is mainly due to the heightened concern and plenty of evidence for inadequate retirement savings brought by a lack of good savings behaviour, which lowered retirement wellbeing among Malaysians (Employees Provident Fund [EPF], 2021). This polemic adds to the population shift complication as more Malaysians who are ill-prepared for retirement will increasingly rely on the government for help and assistance in their retirement years. To avoid or mitigate this issue, there is a need to understand predictors that can enhance retirement preparedness. This is to enable the right parties to structure better policies to enhance retirement preparedness in individuals. Financial counselling and planning professionals, as well as policymakers, have a stake in better understanding the factors that influence a person's retirement preparedness. This research is particularly important considering the governments' increasingly stretched capability in providing an adequate social security infrastructure to individuals. If a data-driven method in the form of a machine learning technique with an underlying basaais in behavioural economics can be used to systematically show and suggest factors that impact a person's retirement preparedness in a wholesome and complete fashion, it may be possible to design a system that improves the level of retirement preparedness among Malaysians.

4.2 Descriptive Analysis of Demography

A total of 3,067 responses were used from the MARS wave 1 survey data from a total number of 5,613 respondents. The reduction in number was due to the 2,546 respondents did not either answer or report their views on retirement (i.e., questions pertaining to how often they think about retirement for those who have yet to retire and questions on life satisfaction in retirement for those who have retired).

The states these respondents came from are as in Table 4.1. While a majority is from the state of Sabah, the number of respondents is evenly spread across the states, consistent with the number of enumerative blocks (EBs) assigned to them as per the original MARS wave 1 survey data set. The number of EBs selected in each state was based on proportionate allocation to the population size of the state, which led to more EBs allocated to states with larger population sizes, such as Johor and Sabah (Mansor et al., 2019).

Table 4.1: State of origin of respondents

State	Frequency (n)	Percentage (%)
Sabah	462	15.1%
Perak	376	12.3%
Johor	357	11.6%
Kedah	331	10.8%
Sarawak	269	8.8%
Kelantan	246	8.0%
Selangor	175	5.7%
Unreported	156	5.1%
Terengganu	156	5.1%
Pahang	144	4.7%
Pulau Pinang	134	4.4%
Negeri Sembilan	102	3.3%
Melaka	82	2.7%
W.P. Kuala Lumpur	46	1.5%
Perlis	27	0.9%
W.P. Labuan	4	0.1%
Total	**3,067**	**100%**

The ages of the respondents for this study remain consistent with MARS survey data where respondents are 40 years old and above, as those below the age of 40 generally do not save at all, are found to be in financial distress, and may not find thinking about retirement to be a top priority. Many spend beyond their means and struggle to pay off their debts (Asian Institute of Finance [AIF], 2015; ICMR, 2021; MFPC, 2018), and including younger respondents would risk skewing the results of the data analysis. A majority of the respondents (33.68%) are in the twilight years of employment and on the verge of retirement.

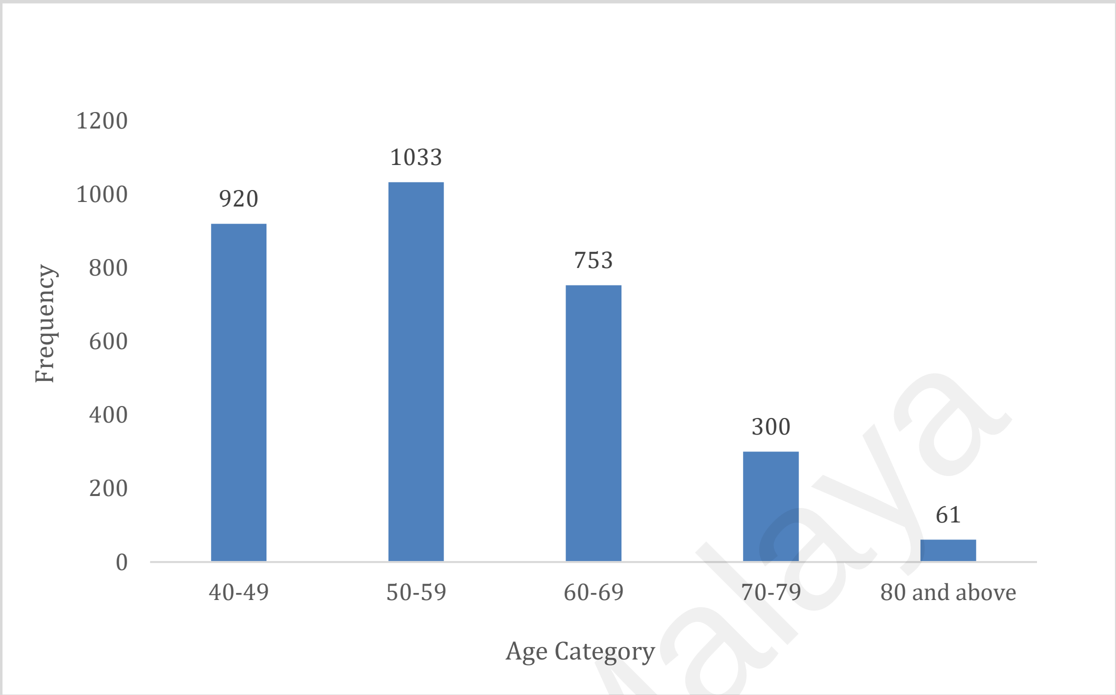


Figure 4.1: Respondents by age category

Out of the number of people who are pre-retirees (2002 respondents), the breakdown of the profession is as below. The majority of the respondents (21.24%) are skilled agricultural, forestry and fishery workers, such as workers in livestock and dairy producer, farm, fishery, forestry, etc., with 425 respondents being in that profession. One respondent chose not to report their occupation.

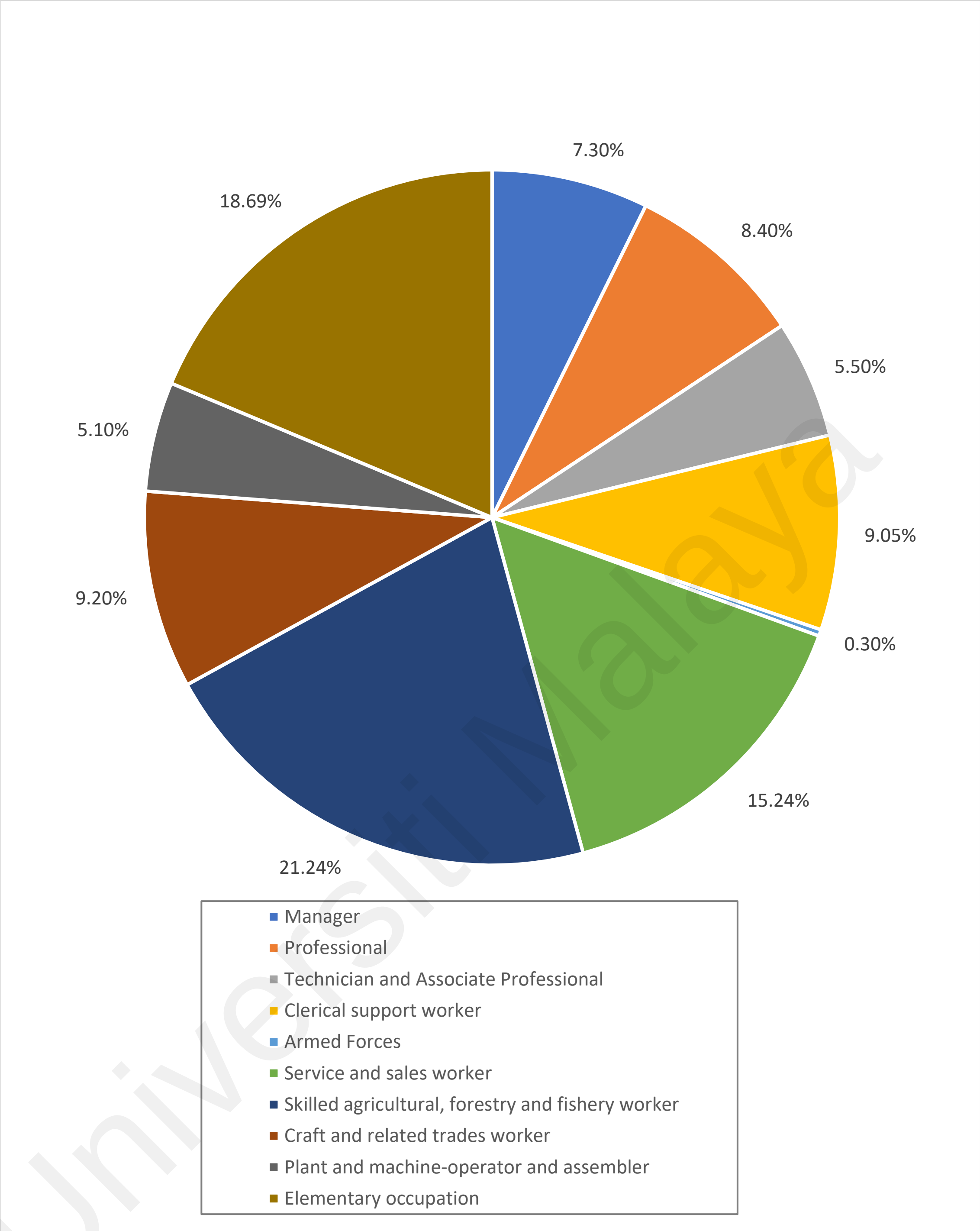


Figure 4.2: Respondents by professional category

The survey questionnaires also captured the respondent's reported household monthly income category. However, this figure is on a reported basis and is not used for further analysis as part of the mental accounting category. For this, the survey questionnaire asked respondents to report their total monthly income after tax, including income from salary, profit from business, remittances, and rental income. However, for this study's analysis on mental accounting, the total annual current income consists of the sum of pension, rental income, salary/income from the business, insurance, allowances from the Social Security Organisation (SOCSO), Social Welfare Department (Elderly/Disability aid), Zakat/donation received, dividend from shares or unit trusts, subsidies/cost of living allowance (Bantuan Sara Hidup), allowance or contribution from Armed Forces Fund Board (LTAT), net intergenerational transfers and others combined in Ringgit Malaysia. A majority (69.65%) reported earning less than RM2,000, whereas 65.04% of pre-retirees and 78.31% are in this category. This approach is consistent with the works of Schooley and Worden (2008). The details for the respondents for their respective reported household income are as below. From this, 65.03% of pre-retirees and 78.31% of retired respondents reported earning less than RM2,000 monthly. 69.64% reported earning less than RM2,000 monthly combined.

Table 4.2: Res ondent's re orted househo d month y income

Total Monthly Income after Tax	**Frequency, (n)** Pre-retirees	**Percentage, (%)**	**Frequency, (n)** Retired	**Percentage (%)**	**Frequency, (n)** Total	**Percentage (%)**
Less than RM1,000	**624**	**31.17**	**595**	**55.87**	**1219**	**39.75**
RM1,000 to RM1,999	**678**	**33.87**	**239**	**22.44**	**917**	**29.90**
RM2,000 to RM2,999	**265**	**13.24**	**126**	**11.83**	**391**	**12.75**
RM3,000 to RM3,999	**153**	**7.64**	**47**	**4.41**	**200**	**6.52**
RM4,000 to RM4,999	**89**	**4.45**	**20**	**1.88**	**109**	**3.55**
RM5,000 to RM5,999	**53**	**2.65**	**19**	**1.78**	**72**	**2.35**
RM6,000 to RM6,999	**35**	**1.75**	**5**	**0.47**	**40**	**1.30**
RM7,000 to RM7,999	**30**	**1.50**	**3**	**0.28**	**33**	**1.08**
RM8,000 to RM8,999	**23**	**1.15**	**3**	**0.28**	**26**	**0.85**
RM9,000 to RM9,999	**11**	**0.55**	**1**	**0.09**	**12**	**0.39**
RM10,000 or more	**40**	**2.00**	**5**	**0.47**	**45**	**1.47**
Unreported	**1**	**0.05**	**2**	**0.19**	**3**	**0.10**
Total	**2002**	**100**	**1065**	**100**	**3067**	**100**

The study also captured the frequency of the person responsible for their finances. The majority have themselves to manage their finances (44.70% combined, 46.30% for pre-retirees, and 41.69% for those who have retired). Another noteworthy finding is that the portion of those who have their children managing their finances differed sharply between pre-retirees (0.80%) and retirees (11.74%).

Table 4.3: Frequency of the person responsible for res ondents’ finances

Who manages your household finances?	Pre-retirees		Retired		Total	
	Frequency (n)	Percentage (%)	Frequency (n)	Percentage (%)	Frequency (n)	Percentage (%)
Mostly own self	927	46.30%	444	41.69%	1371	44.70%
Mostly spouse	289	14.44%	189	17.75%	478	15.59%
Jointly together	736	36.76%	287	26.95%	1023	33.36%
Children	16	0.80%	125	11.74%	141	4.60%
Extended Family	31	1.55%	18	1.69%	49	1.60%
Others	3	0.15%	2	0.19%	5	0.16%
Total	**2002**	**100%**	**1065**	**100%**	**3067**	**100%**

On top of that, another questionnaire asked respondents the extent the respondent can manage their monthly expenditures. Out of 2002 pre-retirees, two did not report on this questionnaire and out of 1065 of those who have retired, two did not report on this questionnaire. Of those pre-retirees, 72.6% reported a scale of more than five, while for those who have retired, 64.16% reported a scale of more than 5. This suggests that a majority of respondents believe that they can manage their monthly expenditures well.

Table 4.4: Sca e for res ondents’ abi ity in managing month y ex en diture

To what extent can you manage your monthly expenditure?	Pre-retirees		Retired		Total	
Scale	**Frequency (n)**	**Percentage (%)**	**Frequency (n)**	**Percentage (%)**	**Frequency (n)**	**Percentage (%)**
1	25	1.3%	31	2.92%	56	1.8%
2	13	0.7%	22	2.07%	35	1.1%
3	37	1.9%	31	2.92%	68	2.2%
4	77	3.9%	54	5.08%	131	4.3%
5	397	19.9%	243	22.86%	640	20.9%
6	357	17.9%	173	16.27%	530	17.3%

Table 4.4, continued

To what extent can you manage your monthly expenditure?	Pre-retirees		Retired		Total	
Scale	**Frequency (n)**	**Percentage (%)**	**Frequency (n)**	**Percentage (%)**	**Frequency (n)**	**Percentage (%)**
7	418	20.9%	193	18.16%	611	19.9%
8	400	20.0%	171	16.09%	571	18.6%
9	106	5.3%	55	5.17%	161	5.3%
10	170	8.5%	90	8.47%	260	8.5%
Total	**2000**	**100%**	**1063**	**100%**	**3063**	**100%**

In the variable selection process, age, gender, ethnicity, education level, marital status, employment status, and household size (taken from number of dependents) are selected for demographic variables. The sample is suitable for this study as those aged 40 and above would have likely gone through a good number of years working for the purpose of this study. The number of female respondents is slightly lower in this sample, where females are 54.3% lesser than male respondents. In terms of ethnicity, Bumiputera make up 78% of the respondents, with Chinese at 11%, Indians at 8%, and others at 3%.

In terms of marital status, 82% of the respondents were married, while 18% were single. In terms of education, more than half received at least a secondary education. However, only 8% have tertiary education. It is worth noting that the percentage of no schooling increases with age, and consequently, the percentage of tertiary education decreases with age. The majority of the respondents are pre-retirees (65%). Lastly, a majority have 1 to 5 dependents (79%).

Table 4.5: Demographic breakdown

Demographic Factors	Frequency (n=3,067)	Percent (%)
Gender		
Female	962	31%
Male	2,105	69%
Ethnic		
Bumiputera	2,402	78%
Chinese	347	11%
Indian	233	8%
Others	85	3%
Marital Status		
Married	2,526	82%
Single	541	18%
Education		
No schooling	190	6%
Primary school	765	25%
Secondary School	1,867	61%
Tertiary	245	8%
Employment Status		
Pre-retiree	2,002	65%
Retired	1,065	35%
Number of Dependents		
1 to 5	2,432	79%
6 to 10	588	19%
11 and above	47	2%

To reduce bias in data, a post-stratification weight readjustment was conducted on the variable gender and ethnic by comparing the population census provided by the Department of Statistics Malaysia in 2018 for citizens above ages 40 years old with the sample data, following advice from SWRC UM. The weight readjustment is as in the table below:

Table 4.6: Weight readjustment for gender and ethnic variable

	Population ("000)	%	Sample	%	Weighting adjustment
Gender					
Male	5,019	50%	2,105	69%	0.72
Female	4963.7	50%	962	31%	1.61
Ethnic					
Bumiputera	5723	57%	2,402	78%	0.74
Chinese	2859.8	29%	347	11%	2.64
Indians	732.9	7%	233	8%	0.88
Others	667	7%	85	3%	2.33

4.3 Analysis on Presence of Mental Accounting Behaviour in Individuals

In this section, an in-depth descriptive analysis was conducted by studying the data of the respondents who have retired. Towards exploring the respondents by separating the pre-retirees and retirees, it is noted that the two groups are statistically similar. Table 4.7 provides an overview of the breakdown of retirees and pre-retirees by demographic variables. It is noted that the two groups are statistically similar.

Table 4.7: Breakdown of retirees and pre-retirees by demographic variables

	Pre-retirees		Retired	
	Frequency	**% Total**	**Frequency**	**% Total**
Gender				
Male	1337	67%	768	72%
Female	665	33%	297	28%
Ethnicity				
Bumi	1605	80%	797	75%

Table 4.7, continued

	Pre-retirees		Retired	
	Frequency	% Total	Frequency	% Total
Chinese	196	10%	151	14%
Indian	139	7%	94	9%
Others	62	3%	23	2%
Marital Status				
Married	1702	85%	824	77%
Single	300	15%	241	23%
Education Level				
No schooling	102	5%	88	8%
Primary school	442	22%	323	30%
Secondary School	1278	64%	589	55%
Tertiary	180	9%	65	6%

The results for the first objective are consolidated as below, where for pre-retirees, 63.5% of respondents are implied to display difference in valuation of gains and losses consistent with Yeh (2020) and Kahneman and Tversky (1979). In one category where as many as 270 respondents displayed good savings behaviour and often think about retirement yet have not achieved adequacy. The segregation of gains (i.e., having good savings behaviour) and loss (i.e., not achieving adequate savings level) is evidenced here, where respondents are shown to think more about retirement, considering that they have yet to achieve savings adequacy despite having good savings behaviour. This is telling in regard to those respondents that showed a behaviour of being loss averse (Shefrin & Thaler, 1988; Townsend, 2018; Yeh, 2020). Separately, it can be suggested that 398 respondents are likely to be loss averse (here, proxied with often thinking about retirement) in the face of bad savings behaviour and lack of adequate savings.

While thinking about retirement idly may not benefit an individual towards retirement preparedness, this behaviour can be channelled towards investing more time and effort towards preparing for retirement. In this regard, behavioural awareness training can complement and enrich financial literacy skills training, where individuals can be trained to leverage this behaviour by further exploring tools and ways to prepare for retirement rather than just thinking about it. Financial and capital market product policy developers can also enhance their platforms and product offerings to leverage this behaviour. For example, a digital investment or robo-advisor can gently nudge an individual thinking about retirement to put the effort to good use by exploring financial products that are designed to enhance their retirement savings adequacy. Consistent with Noone et al. (2010), psychological, social, and health resources on top of savings adequacy are important for a person to be prepared for retirement. In this regard, trained therapists can leverage the loss-averse behaviour to make individuals start strategising on how to sustainably re-orientate their psychological, social and health lifestyle in preparation for retirement. In one way, individuals thinking about retirement can start organising or joining volunteer groups on weekends to build non-work-related relationships and find self-fulfilment by participating in activities outside of their work.

In the next category, as many as 605 respondents exhibit the behaviour of separating the small gain from the large loss. In this category, respondents have good savings behaviour, yet lack adequate savings and do not think about retirement often. Here, respondents put more weight on perceived gain (good savings behaviour) rather than on perceived loss (lack of adequate savings). It can also suggest that respondents exhibit the Dunning-Kruger effect, where they overestimate their savings ability due to their good savings behaviour. While having good savings behaviour is positive, a lot more benefit would come to the individual if she would be able to also review her savings adequacy regularly as retirement approaches. To moderate an individual’s perception of sufficiency due to having good savings behaviour, financial councillors may nudge individuals to allocate time to review their finances to ensure that they are aware of their retirement savings adequacy. In this regard, an overwhelming 63.6% of respondents explicitly exhibit non-monetary mental accounting behaviour.

As for the current retirees, two categories are worth highlighting. Firstly, as many as 245 respondents have good savings behaviour yet do not achieve adequate savings; report that they are satisfied with their retirement and even reported that their life in retirement is good as compared to life prior to retirement. This suggests that respondents put more weight on perceived gain (good savings behaviour) rather than on perceived loss (lack of adequate savings). Meanwhile, as many as 507 respondents who do not have good savings behaviour and did not achieve adequate savings find that they are satisfied with their retirement. Additionally, respondents from this category reported that their life in retirement is good as compared to life prior to retirement. This suggests that they focus on the silver lining, where they segregate perceived gain over a loss. For current retirees, it can be suggested that 70.6% of respondents is suggested to exhibit non-monetary mental accounting behaviour. While life in retirement may be satisfactory for retired respondents, this could be due to the strong psychological, social, and health resources available to the respondents. Despite this, it remains pertinent for individuals to also have strong financial resources sustainably to enable them to live in retirement well. To this end, retirees may well benefit from help given to them by trained financial councillors, where these councillors may be able to advise them to re-orientate their spending and wisely track their income in retirement. A redistribution of asset allocation may well serve retirees who have just entered retirement since they are mostly still healthy and of sound mind. Further, government fiscal and financial support given to programmes such as “Hire.Seniors” capitalising on recent retirees’ ability to work part-time should be expanded as they could use the extra income earned to bolster their financial savings in retirement. Currently, the “Hire.Seniors” programme receives government support in the form of inclusion in the Short-Term Employment Programme (MySTEP), where the salary of employed senior citizens are financed by the government. Moreover, a further deduction is provided by the government for companies that employ senior citizens (60 years and above) or ex-convicts up to a monthly remuneration of RM4,000 (until YA 2025) (PricewaterhouseCoopers [PWC], 2022). To complement this provision, trained councillors must be employed and regulated by the governments as they are needed to help guide senior citizens who are considering joining the workforce partially.

In this regard, an overall 66% of respondents in this study is suggested to exhibit non-monetary mental accounting behaviour. Given that a majority of respondents explicitly exhibit non-monetary mental accounting behaviour, it can be suggested that mental accounting behaviour is apparent in retirement preparedness, where gains and losses are viewed differently. In this regard, this study confirms Hypothesis 1, where mental accounting behaviour is present in retirement preparedness, where gains and losses are viewed differently.

Generally, these descriptive findings are consistent with previous findings where individuals exhibit mental accounting behaviour of viewing gains and losses (Kahneman & Tversky, 1979; Shefrin & Thaler, 1988; Townsend, 2018; Yeh, 2020). Additionally, this behaviour is seen on how individuals view non-monetary goods such as abilities, consistent with Huang et al. (2020). This calls for a better financial literacy tool to leverage this behaviour. Where perceived losses in terms of behaviour are present, financial planners, councillors and therapists would do better by training their clients to be aware of this behaviour and have a contingency plan to mitigate their losses.

Table 4.8: Frequency for combination for presence of mental accounting behaviour in pre-retirees

For Pre-Retirees			
Savings behaviour ***(Objective element of retirement preparedness)***	**Savings adequacy** ***(Objective element of retirement preparedness)***	**How often have you thought about retirement?** ***(Subjective element of retirement preparedness)***	**Frequency**
YES	YES	OFTEN	5
YES	YES	NOT OFTEN	8
YES	NO	OFTEN	270
YES	NO	NOT OFTEN	605
NO	YES	OFTEN	14
NO	YES	NOT OFTEN	12
NO	NO	OFTEN	398
NO	NO	NOT OFTEN	690

Table 4.9: Frequency for combination for presence of mental accounting behaviour in retirees

For Current Retirees				
Savings behaviour ***(Objective element of retirement preparedness)***	**Savings adequacy** ***(Objective element of retirement preparedness)***	**Are you satisfied with your retirement?** ***(Subjective element of retirement preparedness)***	**What would you say about your retirement life compared to before retirement?** ***(Subjective element of retirement preparedness)***	**Frequency**
YES	YES	YES	GOOD	5
YES	YES	YES	NOT GOOD	4
YES	YES	NO	GOOD	1
YES	YES	NO	NOT GOOD	0
YES	NO	YES	GOOD	245
YES	NO	YES	NOT GOOD	25
YES	NO	NO	GOOD	12
YES	NO	NO	NOT GOOD	17
NO	YES	YES	GOOD	15
NO	YES	YES	NOT GOOD	5
NO	YES	NO	GOOD	2
NO	YES	NO	NOT GOOD	0
NO	NO	YES	GOOD	507
NO	NO	YES	NOT GOOD	95
NO	NO	NO	GOOD	61
NO	NO	NO	NOT GOOD	71

In addition to Table 4.8 and Table 4.9, Table 4.10 is provided below to supplement the discussion on mental accounting descriptive analysis, where the average division and allocation by mental accounting categories is dissected by demographic factors. By gender, it is seen that both males and females have their wealth mostly in current asset, despite males have more current income than females on average. Additionally, females have more future income on average than males. Both genders spend most on necessities, but males spend more on necessities than females. Males also tend to spend more on discretionary items than females on average while the opposite is true for luxury items. In this regard, mental accounting allocation differ between male and females.

Further, it is seen that married individuals have more wealth and more expenditure than single individuals across all mental accounting categories. Generally, both married and single individuals have their wealth mostly in current asset and spend most on necessity items. Form this angle, it can be implied here that mental accounting differences is not noted by marital status.

For education level, individuals with secondary school education level have the highest average amount of current asset, while individuals with tertiary education level have more average current income and future income than the rest. Individuals spend on necessity items most regardless of education level. However, individuals with tertiary education level spend more than individuals with lower education level across all expenditure mental accounting category. From this angle, it can be implied that indviduals with tertiary level education should be encouraged to balance wealth accumulation between current asset and future income while individuals with secondary school education level can be encouraged to keep more in future income category.

Lastly, individuals in a household of 8 have the largest average current income while individuals in a household of 17 have the smallest average current income. Individuals in a household of 5 have the largest average current asset while individuals in a household of 14 and above have the smallest average current income. Individuals in a household of 9 have the largest average future income while individuals in a household of 14,16, and 20 have the smallest average future income. It can be implied that higher household size negatively impacts the amount of wealth across mental accounting categories. It can also be noted that individuals have most of their wealth in current asset category rather than the current income or future income. Meanwhile, households of 14 have highest average expenditure on necessity items while households of 1 have lowest average expenditure on necessity items. The opposite holds true for discretionary items and luxury items. Households of 6 have highest average expenditure on necessity items while households of 17 have lowest average expenditure on discretionary items. Households of 6 have highest average expenditure on luxury items while households of 16 and 17 have lowest average expenditure on necessity items This suggests that mental accounting categories allocation differ by size of household.

Table 4.10: Average allocation of mental accounting categories (RM) by demographic factors

	Average Total Current Income	Average Total Current Asset	Average Total Future Income	Average Necessities Expenditure	Average Discretionary Item Expenditure	Average Luxury Item Expenditure
Gender						
Male	13,396.59	101,521.55	34,526.99	779.98	227.31	79.85
Female	11,770.25	2,230,839.39	40,437.85	608.94	214.66	83.91
Marital Status						
Married	13,035.81	904,902.55	38,277.45	777.07	232.08	83.55
Single	12,189.17	136,758.77	27,526.21	489.42	182.53	69.80
Education Level						
No schooling	4,955.63	34,013.16	13,633.42	423.15	103.92	12.90
Primary school	7,909.23	78,204.95	14,047.42	532.27	106.38	42.03
Secondary School	12,670.82	1,192,564.63	42,466.55	757.93	226.41	80.53
Tertiary	36,221.40	273,317.96	77,383.04	1,326.64	657.81	260.62
Household Size						
1	11,788.98	117,743.46	21,544.55	575.29	180.23	75.29
2	14,180.98	131,139.55	11,960.45	655.91	253.42	74.66
3	12,915.24	101,453.72	28,540.37	757.67	219.53	87.44

Table 4.10, continued

	Average Total Current Income	Average Total Current Asset	Average Total Future Income	Average Necessities Expenditure	Average Discretionary Item Expenditure	Average Luxury Item Expenditure
Household Size						
4	13,118.08	89,640.15	31,186.06	823.32	232.96	74.98
5	13,297.99	5,451,573.80	25,818.59	781.28	196.86	79.54
6	13,044.08	171,466.85	69,787.14	806.74	327.73	125.25
7	11,572.10	151,176.83	19,747.26	762.01	201.91	65.12
8	18,369.19	174,256.76	15,481.08	832.35	251.80	86.32
9	10,414.98	78,396.23	582,951.00	790.91	141.51	70.74
10	6,681.48	125,555.56	19,114.81	800.26	164.22	19.52
11	4,771.67	10,555.56	4,016.67	799.61	129.78	99.72
12	16,648.89	47,777.78	12,605.56	741.44	113.33	32.89
13	4,612.50	12,500.00	3,437.50	828.25	65.00	51.13
14	912.50	-	-	1,046.25	61.25	88.75
16	3,050.00	-	-	395.00	64.00	70.40
17	250.00	-	8,500.00	315.00	50.00	-
20	18,000.00	-	-	1,020.00	398.00	-

4.4 Model Outcome for Predicting Retirees' Retirement Satisfaction

To compare pre-retirees' retirement thinking, and retirees' retirement satisfaction in terms of mental accounting allocation predictive power, two set of machine learning models are developed where one is developed to predict retirement satisfaction, and the other is to predict the tendency to think about retirement. The first machine learning model results can then be compared to the second machine learning model results, where features that hold predictive power on retirement satisfaction would be compared to features that hold predictive power on the tendency to think about retirement. In this section, the outcome of the machine learning model used to predict retirement satisfaction is presented.

Table 4.11: Performance of retirement satisfaction machine learning models

	NB	GLM	LR	ANN	DT	RF	GBT
Accuracy	80.30%	80.30%	80.30%	80.30%	80.00%	80.00%	80.30%
Classification Error	19.70%	19.70%	19.70%	19.70%	20.00%	20.00%	19.70%
AUC	50.80%	58.60%	60.50%	64.70%	49.80%	65.10%	47.80%
Precision	80.30%	80.30%	80.30%	80.30%	80.30%	80.30%	80.30%
Recall	100.00%	100.00%	100.00%	100.00%	99.60%	99.60%	100.00%
F measure	89.10%	89.10%	89.10%	89.10%	88.90%	88.90%	89.10%
Specificity	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%	0.00%

Table 4.12: Predictive power of attributes on retirement satisfaction machine learning models

	NB	GLM	LR	ANN	DT	RF	GBT
Mental Accounting Categories for Wealth							
Current Income	0.026	0.189	0.180	0.336	0.000	0.234	0.027
Current Asset	0.014	0.017	0.017	0.021	0.000	0.085	0.067
Future Income	0.046	0.683	0.687	0.633	0.000	0.555	0.374
Mental Accounting Categories for Expenditure							
Necessities	0.009	0.060	0.060	0.073	0.000	0.042	0.130
Discretionary Items	0.016	0.132	0.130	0.112	0.000	0.315	0.071
Luxury Items	0.027	0.017	0.016	0.014	0.001	0.019	0.008

Table 4.12, continued

	NB	GLM	LR	ANN	DT	RF	GBT
Demographics							
Age	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Male	0.053	0.012	0.011	0.009	0.001	0.010	0.071
Female	0.040	0.033	0.000	0.026	0.000	0.008	0.040
Bumiputera	0.050	0.104	0.100	0.104	0.000	0.135	0.246
Chinese	0.020	0.031	0.030	0.034	0.000	0.017	0.039
Indian	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Others	0.000	0.000	0.000	0.000	0.000	0.000	0.000
No schooling	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Primary School	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Secondary School	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Tertiary Education	0.042	0.056	0.000	0.054	0.000	0.044	0.000
Single	0.000	0.000	0.056	0.000	0.000	0.000	0.000
Married	0.087	0.056	0.000	0.049	0.000	0.057	0.010
Household size	0.013	0.004	0.005	0.024	0.000	0.028	0.092

Note. NB = Naïve Bayes; GLM = Generalised Linear Model; LR = Logistic Regression, DL = Deep Learning; DT = Decision Tree; RF = Random Forest; and GBT = Gradient Boosted Trees.

4.4.1 Naïve Bayesian

The Naïve Bayesian model that predicts retirement satisfaction performed well with accuracy reaching 80.33%, where AUC achieved 50.8%, precision reaching 80.30%, recall at 100% and F measure at 89.10%.

In the Naïve Bayesian model, it was found that total future income has the highest predictive weightage to retirement satisfaction, followed by total current income. It can be suggested that best mental accounting allocation that can bring about retirement satisfaction is weighted most by total future income, total annual current income, and total current assets for wealth allocation. Total current asset is the lowest as assets are not as liquid as income in an imperfect market. Hence, it does not rank highly in predicting retirement satisfaction. Meanwhile, expenditure is on luxury items, discretionary items, and total necessities accordingly.

From a demographic perspective, it is observed that Bumiputras generally have a higher probability of satisfaction in retirement, followed by Chinese. Meanwhile, marital status has a higher weightage than education and household size. Being male would entail a higher probability of being satisfied in retirement than females. The rest of the features are below 0.000, which signals low weightage in predicting retirement satisfaction. It must be noted that the fundamental assumption of Naive Bayes is that, given the value of the label (the dependent variable), the value of any independent variable is independent of the value of any other independent variable. Strictly speaking, this assumption is rarely true (hence, the usage of the term "naïve"). The independence assumption vastly simplifies the calculations needed to build the Naive Bayes probability model. However, caution must be taken in analysing data which may contain behavioural elements as it is not necessary that each independent variable is independent from another independent variable.

4.4.2 Generalised Linear Model

The Generalised Linear model that predicts retirement satisfaction performed well with accuracy reaching 80.30%, where AUC achieved 58.6%, precision reaching 80.30%, recall at 100% and F measure at 89.10%. The generalised linear model result is presented as below:

Table 4.13: Generalised linear model result for predicting retirement satisfaction

	Coefficients	Standard Error	t Stat	P-value
Intercept	1.122	0.130	2.490	0.013
Current Income	0.000	0.000	2.756	0.006
Current Asset	(0.000)	0.000	0.703	0.482
Future Income	0.000	0.000	0.184	0.854
Necessities	0.000	0.000	(0.030)	0.976
Discretionary Items	0.000	0.000	(1.296)	0.195
Luxury Items	(0.000)	0.000	0.547	0.584
Age	0.000	0.001	4.663	0.000
Gender (Male)*	(0.023)	0.026	(1.361)	0.174
Ethnic (Bumiputera)*	0.648	0.074	0.613	0.540
Ethnic (Chinese)*	0.002	0.079	0.029	0.977
Ethnic (Indian)*	(0.227)	0.081	(2.784)	0.005
Education Level (Tertiary)*	0.037	0.017	2.226	0.026
Marital Status (Married)*	(0.167)	0.029	1.647	-
Household size	0.079	0.004	(1.125)	0.261

*Reference group for categorical variable as in the parentheses

From this model's outcome, it was found that Current Income, Age, Ethnic (Indian), and education level was statistically significant at 95% confidence interval. However, the R-square value for this model was 0.08 which indicates that the predictors explain less of the variance in the dependent variable. Hence, rendering this model to be unsuitable to model retirement satisfaction.

In such cases, it becomes pertinent to explore alternative methods to assess the importance or significance of the predictor which brings to the RapidMiner's independent variable importance ranking, which allows for the understanding of which variable contributing the most to the model's predictions. By examining this ranking, it is possible to identify the variables that have the strongest association with the target variable. In the Generalised Linear model, it was found that total future income has the highest predictive weightage to retirement satisfaction, followed by total current income. It can be suggested that the best mental accounting allocation that can bring about retirement satisfaction is weighted most by total future income, total annual current income, and total current assets for wealth allocation. Total current asset is the lowest as assets are not as liquid as income in an imperfect market. Hence, it does not rank highly in predicting retirement satisfaction. Meanwhile, expenditure is on luxury items, discretionary items, and total necessities accordingly.

From a demographic perspective, it is observed that Bumiputras generally have a higher probability of satisfaction in retirement, followed by Chinese. Meanwhile, marital status has a higher weightage than education and household size. Being male would entail a higher probability of being satisfied in retirement than females. The rest of the features are below 0.000, which signals low weightage in predicting retirement satisfaction.

4.4.3 Logistic Regression

The Logistic Regression model that predicts retirement satisfaction performed well with accuracy reaching 80.30%, where AUC achieved 60.5%, precision reaching 80.30%, recall at 100% and F measure at 89.10%. The Logistic Regression model result is presented as below:

Table 4.14: Logistic regression model result for predicting retirement satisfaction

	Beta	Standard Error	Wald	P-value
Intercept	-2.424	0.000	0.110	0.089
Current Income	0.000	0.000	17.160	0.000
Current Asset	0.000	0.000	0.797	0.372
Future Income	0.000	0.000	0.000	0.988
Necessities	0.000	0.000	0.459	0.498
Discretionary Items	0.000	0.001	0.056	0.813
Luxury Items	0.001	0.000	0.432	0.511
Age	0.048	0.011	0.000	1.049
Gender (Male)*	0.283	0.220	0.198	1.328
Ethnic (Bumiputera)*	(0.243)	0.584	0.677	0.784
Ethnic (Chinese)*	0.011	0.625	0.985	1.012
Ethnic (Indian)*	1.341	0.619	0.030	3.824
Education Level (Tertiary)*	(0.540)	0.457	0.793	0.887
Marital Status (Married)*	(0.268)	0.229	0.243	0.765
Household size	(0.040)	0.036	0.272	0.961

*Reference group for categorical variable as in the parentheses

From this model's outcome, it was found that only Current Income was statistically significant at 95% confidence interval. In addition, the Cox and Snell R-square value for this model was 0.088 while the Nagelkerk R Square was 0.152 which indicates that the predictors explain less of the variance in the dependent variable. Hence, rendering this model to be unsuitable to model retirement satisfaction. Proper interpretation requires considering the context, knowledge, and the specific goals of the analysis to make informed conclusions about the model's fit and predictive power.

In such cases, it becomes pertinent to explore alternative methods to assess the importance or significance of the predictor which brings to the RapidMiner's independent variable importance ranking, which allows for the understanding of which variable contributing the most to the model's predictions. By examining this ranking, it is possible to identify the variables that have the strongest association with the target variable. In the Logistic Regression model, it was found that total future income has the highest predictive weightage to retirement satisfaction, followed by total current income. It can be suggested that the best mental accounting allocation that can bring about retirement satisfaction is weighted most by total future income, total annual current income, and total current assets for wealth allocation. Total current asset is the lowest as assets are not as liquid as income in an imperfect market. Hence, it does not rank highly in predicting retirement satisfaction. Meanwhile, expenditure is on discretionary items, necessities items, and luxury items accordingly.

From a demographic perspective, it is observed that Bumiputras generally have a higher probability of satisfaction in retirement, followed by Chinese. Meanwhile, household size has a higher weightage than education and marital status. Being male would entail a higher probability of being satisfied in retirement than females. The rest of the features are below 0.000, which signals low weightage in predicting retirement satisfaction.

4.4.4 Artificial Neural Network

The artificial neural network model that predicts retirement satisfaction performed well with accuracy reaching 80.33%, where AUC achieved 64.5%, precision reaching 80.33%, recall at 100% and F measure at 89.10%. In this regard, ANN is a good model that can be used to predict retirement satisfaction.

In the ANN model, it was found that total future income has the highest predictive weightage to retirement satisfaction, followed by total current income. It can be suggested that the best mental accounting allocation that can bring about retirement satisfaction is weighted most by total future income, total annual current income, and total current assets for wealth allocation. Total current asset is the lowest as assets are not as liquid as income in an imperfect market. Hence, it does not rank highly in predicting retirement satisfaction. Meanwhile, expenditure is on discretionary items, total necessities, and luxury items accordingly.

From a demographic perspective, it is observed that Bumiputras generally have a higher probability of satisfaction in retirement, followed by Chinese. Meanwhile, education has a higher weightage than marital status and household size. Being female would entail a higher probability of being satisfied in retirement than males. The rest of the features are not reported, given that the weightage is below 0.00, which signals low weightage in predicting retirement satisfaction. In comparison to other models, it was found that ANN performed as well, if not better, than most of the other models.

4.4.5 Decision Tree

The Decision Tree model that predicts retirement satisfaction performed with accuracy reaching 80.00%, where AUC achieved 49.8%, precision reaching 80.30%, recall at 99.60% and F measure at 88.90%. In this regard, Decision Tree model can be used to predict retirement satisfaction. The Decision Tree model is presented as below:

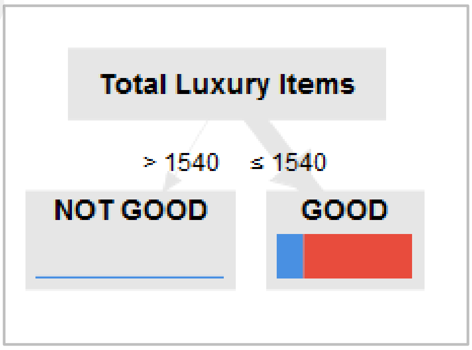


Figure 4.3: Decision Tree for Predicting Retirement Satisfaction Result

The small number of branches could be owed to possibility of the data set being imbalanced and complex to predict. In this case, for each modelling algorithm, predicting the class of interest (yes to being satisfied in retirement) will be the best choice. Therefore, having imbalanced data is not necessarily a problem, as balancing the data before running the model would not give a perfect model for deployment. It remains important that validation of models is done on the original (imbalanced) distribution even when using some sampling method to build better models.

In such cases, it becomes pertinent to explore alternative methods to assess the importance or significance of the predictor which brings to the RapidMiner's independent variable importance ranking, which allows for the understanding of which variable contributing the most to the model's predictions. By examining this ranking, it is possible to identify the variables that have the strongest association with the target variable. In the Decision Tree model, it was found that current income has the highest predictive weightage to retirement satisfaction, followed by current asset. It can be suggested that the best mental accounting allocation that can bring about retirement satisfaction is weighted most by total current income, total annual current asset, and total future income for wealth allocation. Meanwhile, expenditure is on luxury items, necessities items, and discretionary items accordingly.

From a demographic perspective, it is observed that Bumiputras generally have a higher probability of satisfaction in retirement, followed by Chinese. Meanwhile, education size has a higher weightage than household and marital status. Being male would entail a higher probability of being satisfied in retirement than females. For the Decision tree model, only luxury items and being male had predictive power of more than 0.000 where the rest of the features are below 0.000, which signals low weightage in predicting retirement satisfaction. In this regard, the Decision Tree model is a weak model at predicting retirement satisfaction.

4.4.6 Random Forest

The Random Forest model that predicts retirement satisfaction performed with accuracy reaching 80.00%, where AUC achieved 65.10%, precision reaching 80.30%, recall at

99.60% and F measure at 88.90%. In this regard, Random Forest is a good model that can be used to predict retirement satisfaction. A single decision tree within the Random Forest model is presented as below, as the whole Random Forest is made up of 100 trees which may not be viable to presented in this study:

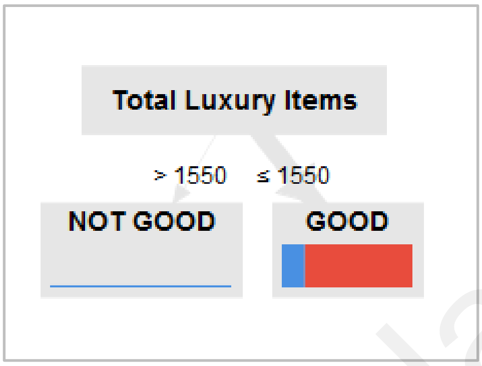


Figure 4.4: Single Decision Tree from Random Forest Model for Predicting Retirement Satisfaction

The small number of branches could be owed to possibility of the data set being imbalanced and complex to predict. In this case, for each modelling algorithm, predicting that the majority class (yes to being satisfied in retirement) will be the best choice. Therefore, having imbalanced data is not necessarily a problem, as balancing the data before running the model would not give a perfect model for deployment. It remains important that validation of models is done on the original (imbalanced) distribution even when using some sampling method to build better models.

In such cases, it becomes pertinent to explore alternative methods to assess the importance or significance of the predictor which brings to the RapidMiner's independent variable importance ranking, which allows for the understanding of which variable contributing the most to the model's predictions. By examining this ranking, it is possible to identify the variables that have the strongest association with the target variable. In the Random Forest model, it was found that future income has the highest predictive weightage to retirement satisfaction, followed by current income. It can be suggested that the best mental accounting allocation that can bring about retirement satisfaction is weighted most by total future income, total annual current income, and total current asset for wealth allocation. Meanwhile, expenditure is on discretionary items, necessities items, and luxury items accordingly.

From a demographic perspective, it is observed that Bumiputras generally have a higher probability of satisfaction in retirement, followed by Chinese. Meanwhile, marital status has a higher weightage than education and household size. Being male would entail a higher probability of being satisfied in retirement than females. For the Random Forest model, the rest of the features are below 0.000, which signals low weightage in predicting retirement satisfaction.

4.4.7 Gradient Boosted Trees

The Gradient Boosted Trees model that predicts retirement satisfaction performed with accuracy reaching 80.30%, where AUC achieved 47.80%, precision reaching 80.30%, recall at 100% and F measure at 89.10%. In this regard, Gradient Boosted Trees can be used to predict retirement satisfaction. A single decision tree within the Gradient Boosted Trees model is presented as below, as the whole Gradient Boosted Trees is made up of 30 trees which may not be viable to presented in this study:

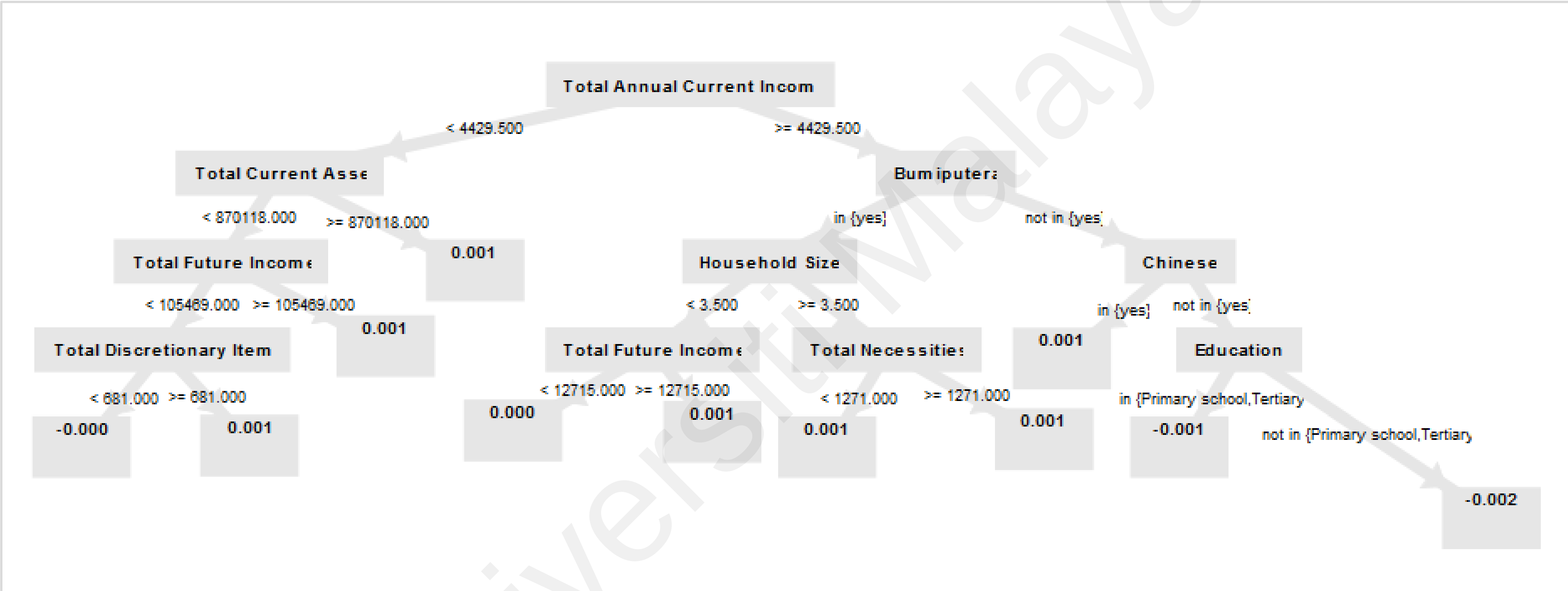


Figure 4.5: Single Decision Tree from Gradient Boosted Trees Model for Predicting Retirement Satisfaction

In the Gradient Boosted Trees model, it was found that future income has the highest predictive weightage to retirement satisfaction, followed by current asset. It can be suggested that the best mental accounting allocation that can bring about retirement satisfaction is weighted most by total future income, total annual current asset, and total current income for wealth allocation. Meanwhile, expenditure is on necessities items, discretionary items, and luxury items accordingly.

From a demographic perspective, it is observed that Bumiputras generally have a higher probability of satisfaction in retirement, followed by Chinese. Meanwhile, household has a higher weightage than marital status and education size. Being male would entail a higher probability of being satisfied in retirement than females. For the Random Forest model, the rest of the features are below 0.000, which signals low weightage in predicting retirement satisfaction.

4.5 Analysis on Retirement Satisfaction

In this regard, this study confirms Hypothesis 2, where mental accounting attributes do have predictive power on retirement satisfaction. However, upon assessment of all the models, it is suggested that the ANN is the most suitable model for predicting retirement satisfaction. This is as standard statistical analysis such as logistic regression could not model retirement satisfaction due to its low R-square measurement which relates to lack of goodness of fit of the models. This entails the models' inability to model retirement satisfaction. However, this should not be taken as a signal that there is no relationship between independent variables and dependent variable. In this regard, machine leaning models are used as an on-par alternative to standard statistical analysis (Garibay et al, 2022). However, other machine learning models such as Naïve Bayesian, Decision Tree, Random Forest, and Gradient Boosted Trees had weaknesses which was not observed in ANN such as independence assumption, small number of branches which could influence predictive outcome, low predictive power among attributes and low AUC value. As such, the outcome for the ANN model is referred to for this study to answer objective 2.

With the exception of Random Forest model, it was observed that future income held most predictive power to retirement satisfaction for wealth component of mental accounting categories. Meanwhile, discretionary items held most predictive power on retirement satisfaction for Generalised Linear Model, Logistic Regression model, ANN model and Random Forest model. While reference to the outcome of the ANN model as the best suited model, it can be suggested that the current retirement savings infrastructure should be focused on the investment of savings in high-return investments, while balancing investment risk, especially for younger retirees such as those who have just entered retirement. This is in line with the Malaysian government's aspiration to alleviate the retirement well-being of Malaysians. While necessities should naturally come first, it is found that expenditure on discretionary items gives more satisfaction in retirement. Discretionary items refer to the cost of telephone/mobile phone/prepaid, toiletries, house repairs and others combined in Ringgit Malaysia. This suggests that expenditure on these items would entail retirees having the same or higher living standards as before retirement, which brings them more satisfaction than expenditure on necessities. While this finding indicates spending on discretionary items holds the most weightage on retirement satisfaction, the importance of the best personal financial budgeting must be advocated by relevant parties. For example, a public-private partnership under the auspices of the Financial Education Network (FEN) can start workshops for community leaders to train them towards better personal financial budgeting, which they can later share with their respective communities. For example, FEN members can collaborate with pensioner's associations to give bite-sized budgeting tips and tricks for spending in retirement, which they can later teach to their members.

Similar performance is observed across all models' performance metrics as the data set is imbalanced and complex to predict. In this case, for each modelling algorithm, predicting that the majority class (yes to being satisfied in retirement) will be the best choice. Therefore, having imbalanced data is not necessarily a problem, as balancing the data before running the model would not give a perfect model for deployment. It remains important that validation of models is done on the original (imbalanced) distribution even when using some sampling method to build better models.

4.6 Model Outcome for Predicting Pre-Retirees' Retirement Thinking

Following section 4.4 Model Outcome for Predicting Retirees' Retirement Satisfaction and section 4.5 Discussion on Objective 2, the outcome of the machine learning model used to predict tendency of thinking about retirement is presented.

Table 4.15: Performance of tendency of thinking about retirement machine learning models

	NB	GLM	LR	ANN	DT	RF	GBT
Accuracy	34.20%	65.80%	65.80%	65.80%	66.20%	58.60%	65.80%
Classification Error	65.80%	34.20%	34.20%	34.20%	33.80%	41.40%	34.20%
AUC	52.20%	61.40%	60.50%	53.80%	50.20%	54.50%	52.20%
Precision	-	65.80%	65.80%	65.80%	66.10%	67.90%	65.80%
Recall	0.00%	100.00%	100.00%	100.00%	99.70%	70.30%	100.00%
F measure	-	79.40%	79.40%	79.40%	79.50%	69.00%	79.40%
Specificity	100.00%	0.00%	0.00%	0.00%	1.50%	36.80%	0.00%

Table 4.16: Predictive power of attributes on tendency of thinking about retirement machine learning models

	NB	GLM	LR	ANN	DT	RF	GBT
Mental Accounting Categories for Wealth							
Current Income	0.216	0.067	0.044	0.116	0.022	0.062	0.100
Current Asset	0.017	0.230	0.310	0.124	0.023	0.271	0.041
Future Income	0.091	0.041	0.008	0.060	0.010	0.009	0.021
Mental Accounting Categories for Expenditure							
Necessities	0.057	0.030	0.001	0.033	0.065	0.037	0.061
Discretionary Items	0.026	0.187	0.017	0.131	0.216	0.102	0.056
Luxury Items	0.031	0.104	0.023	0.000	0.058	0.075	0.154

Table 4.16, continued

	NB	GLM	LR	ANN	DT	RF	GBT
Demographics							
Age	0.031	0.003	0.000	0.083	0.000	0.003	0.095
Male	0.131	0.069	0.025	0.029	0.014	0.038	0.031
Female	0.098	0.123	0.032	0.116	0.014	0.031	0.033
Bumiputera	0.071	0.071	0.056	0.010	0.038	0.011	0.158
Chinese	0.048	0.010	0.016	0.021	0.033	0.004	0.032
Indian	0.037	0.045	0.036	0.054	0.017	0.035	0.057
Others	0.026	0.037	0.019	0.000	0.049	0.044	0.060
No schooling	0.000	0.001	0.000	0.000	0.000	0.000	0.000
Primary School	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Secondary School	0.000	0.058	0.000	0.000	0.000	0.033	0.000
Tertiary Education	0.135	0.000	0.015	0.034	0.000	0.000	0.027
Single	0.000	0.002	0.000	0.000	0.000	0.000	0.000
Married	0.000	0.077	0.000	0.000	0.042	0.016	0.045
Household size	0.019	0.003	0.037	0.061	0.009	0.000	0.078

Note. NB = Naïve Bayes; GLM = Generalised Linear Model; LR = Logistic Regression, DL = Deep Learning; DT = Decision Tree; RF = Random Forest; and GBT = Gradient Boosted Trees.

4.6.1 Naïve Bayesian

The Naïve Bayesian model that predicts tendency of thinking about retirement performed with accuracy reaching 34.20%, where AUC achieved 52.2%, precision at null, recall at 0.00% and F measure at null. In this regard, the Naïve Bayesian is deemed not a suitable model to predict tendency of thinking about retirement.

In the Naïve Bayesian model, it was found that total current income has the highest predictive weightage to tendency of thinking about retirement, followed by total future income. This model suggests that the best mental accounting allocation that can bring tendency of thinking about retirement is weighted most by total current income, total future income, and total current assets for wealth allocation. Total current asset is the lowest as assets are not as liquid as income in an imperfect market. Hence, it does not rank highly in predicting tendency of thinking about retirement. Meanwhile, expenditure is on total necessities, luxury items, and discretionary items accordingly.

From a demographic perspective, it is observed that Bumiputras generally have a higher predictability of thinking about in retirement, followed by Chinese. Meanwhile, education has a higher weightage than marital status and household size. Being male would entail a higher predictability of thinking about retirement than females. The rest of the features are below 0.000, which signals low weightage in predicting tendency of thinking about retirement. It must be noted that the fundamental assumption of Naive Bayes is that, given the value of the label (the dependent variable), the value of any independent variable is independent of the value of any other independent variable. Strictly speaking, this assumption is rarely true (hence, the usage of the term "naïve"). The independence assumption vastly simplifies the calculations needed to build the Naive

Bayes probability model. However, caution must be taken in analysing data which may contain behavioural elements as it is not necessary that each independent variable is independent from another independent variable. In addition, this particular Naïve Bayesian model did not perform up to mark for this study in terms of its assessment metrics.

4.6.2 Generalised Linear Model

The Generalised Linear model that predicts tendency of thinking about retirement performed well with accuracy reaching 65.80%, where AUC achieved 61.4%, precision reaching 65.80%, recall at 100% and F measure at 79.40%. The generalised linear model is presented as below:

Table 4.17: Generalised linear model result for predicting tendency of thinking about retirement

	Coefficients	Standard Error	t Stat	P-value
Intercept	0.034	0.110	0.312	0.755
Current Income	(0.000)	0.000	(0.060)	0.952
Current Asset	0.000	0.000	1.322	0.186
Future Income	0.000	0.000	2.486	0.013
Necessities	0.000	0.000	0.919	0.358
Discretionary Items	0.000	0.000	2.184	0.029
Luxury Items	0.000	0.000	2.104	0.036
Age	0.003	0.001	2.191	0.029
Gender (Male)*	(0.108)	0.023	(4.624)	0.000
Ethnic (Bumiputera)*	0.088	0.042	2.105	0.035
Ethnic (Chinese)*	(0.033)	0.052	(0.637)	0.524
Ethnic (Indian)*	-	-	65,535.000	-
Education Level (Tertiary)*	0.014	0.018	0.824	0.410
Marital Status (Married)*	0.095	0.031	3.056	0.002
Household size	(0.001)	0.005	(0.205)	0.838

*Reference group for categorical variable as in the parentheses

From this model's outcome, it was found that Future Income, Discretionary Items, Luxury Items, Age, Gender (Male), Ethnic (Bumiputera), and marital status was statistically significant at 95% confidence interval. However, the R-square value for this model was 0.03 which indicates that the predictors explain less of the variance in the dependent variable. Hence, rendering this model to be unsuitable to model tendency of thinking about retirement.

In such cases, it becomes pertinent to explore alternative methods to assess the importance or significance of the predictor which brings to the RapidMiner's independent variable importance ranking, which allows for the understanding of which variable contributing the most to the model's predictions. By examining this ranking, it is possible to identify the variables that have the strongest association with the target variable. In the Generalised Linear model, it was found that total current asset has the highest predictive weightage to thinking about retirement, followed by total current income. It can be suggested that the best mental accounting allocation that can bring about the behaviour of often thinking about retirement is weighted most by total current assets, total annual current income, and total future income for wealth allocation. Meanwhile, expenditure is on discretionary items, luxury items, and total necessities accordingly.

From a demographic perspective, it is observed that Bumiputras generally have a higher predictability in tendency of thinking about retirement, followed by Indians. Meanwhile, marital status has a higher weightage than education and household size. Being female would entail a higher predictability in tendency of thinking about retirement than males.

4.6.3 Logistic Regression

The Logistic Regression model that predicts tendency of thinking about retirement performed well with accuracy reaching 65.80%, where AUC achieved 60.50%, precision reaching 65.80%, recall at 100% and F measure at 79.40%. The Logistic Regression model is presented as below:

Table 4.18: Logistic model result for predicting tendency of thinking about retirement

	Beta	Standard Error	Wald	P-value
Intercept	-2.579	0.817	9.967	0.002
Current Income	0.000	0.000	0.001	0.980
Current Asset	0.000	0.000	0.005	0.942
Future Income	0.000	0.000	5.146	0.023
Necessities	0.000	0.000	0.342	0.559
Discretionary Items	0.000	0.000	3.834	0.050
Luxury Items	0.001	0.000	3.455	0.063
Age	0.015	0.007	5.208	0.022
Gender (Male)*	0.485	0.106	21.060	0.000
Ethnic (Bumiputera)*	(0.094)	0.282	0.110	0.740
Ethnic (Chinese)*	0.505	0.327	2.388	0.122
Ethnic (Indian)*	0.318	0.336	0.896	0.002
Education Level (Tertiary)*	0.061	0.081	0.564	0.452
Marital Status (Married)*	(0.456)	0.149	9.409	0.765
Household size	(0.003)	0.021	0.026	0.872
*Reference group for categorical variable as in the parentheses				

From this model's outcome, it was found that only Discretionary Items, Gender, and Ethnic (Indian) was statistically significant at 95% confidence interval. In addition, the Cox and Snell R-square value for this model was 0.034 while the Nagelkerk R Square was 0.047 which indicates that the predictors explain less of the variance in the dependent variable. Hence, rendering this model to be unsuitable to model tendency of thinking about retirement. Proper interpretation requires considering the context, domain knowledge, and the specific goals of the analysis to make informed conclusions about the model's fit and predictive power.

In such cases, it becomes pertinent to explore alternative methods to assess the importance or significance of the predictor which brings to the RapidMiner's independent variable importance ranking, which allows for the understanding of which variable contributing the most to the model's predictions. By examining this ranking, it is possible to identify the variables that have the strongest association with the target variable. In the Logistic Regression model, it was found that total current asset has the highest predictive weightage to tendency of thinking about retirement, followed by total current income. It can be suggested that the best mental accounting allocation that can bring about tendency of thinking about retirement is weighted most by total current assets, total annual current income, and total future income for wealth allocation. Meanwhile, expenditure is on luxury items, discretionary items, and necessities items accordingly.

From a demographic perspective, it is observed that Bumiputras generally have a higher predictability on tendency of thinking about retirement, followed by Indian. Meanwhile, household size has a higher weightage than education and marital status. Being female would entail a higher probability of being satisfied in retirement than females. The rest of the features are below 0.000, which signals low weightage in predicting tendency of thinking about retirement.

4.6.4 Artificial Neural Network

The artificial neural network model, which predicts the tendency to think about retirement, performed well with accuracy reaching 65.80%, where AUC achieved 53.80%, precision reaching 65.80%, recall at 100% and F measure at 79.40%. In this regard, ANN is a good model that can be used to predict the tendency to think about retirement.

In this ANN model, it was found that total current assets have the highest weightage to the tendency to think about retirement, followed by total current income. Meanwhile, expenditure weightage is on discretionary items, total necessities, and luxury items, accordingly. From a demographic perspective, females tend to think about retirement more than males. Age, followed by household size, employment status, and education, has weightage on the tendency to consider retirement accordingly. Indians have more tendency to think about retirement than Chinese and Bumiputera. While the majority of respondents (65.6%) do not often think about retirement, the class of interest for this study's analysis is often thinking about retirement. In this regard, the ANN model can predict tendency to think about retirement.

4.6.5 Decision Tree

The Decision Tree model, which predicts the tendency to think about retirement, performed well with accuracy reaching 66.20%, where AUC achieved 50.20%, precision reaching 66.10%, recall at 99.70% and F measure at 79.50%. In this regard, Decision Tree is a good model that can be used to predict the tendency to think about retirement. The Decision Tree model is presented as below:

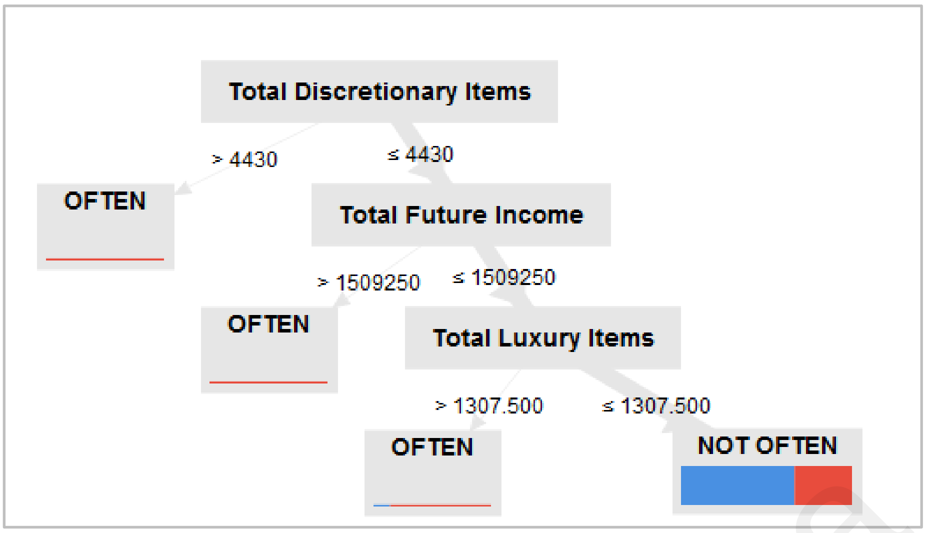


Figure 4.6: Decision Tree for Predicting Tendency of Thinking About Retirement

The small number of branches could be owed to possibility of the data set being imbalanced and complex to predict. In this case, for each modelling algorithm, predicting the class of interest (often think about retirement) will be the best choice. Therefore, having imbalanced data is not necessarily a problem, as balancing the data before running the model would not give a perfect model for deployment. It remains important that validation of models is done on the original (imbalanced) distribution even when using some sampling method to build better models.

In such cases, it becomes pertinent to explore alternative methods to assess the importance or significance of the predictor which brings to the RapidMiner's independent variable importance ranking, which allows for the understanding of which variable contributing the most to the model's predictions. By examining this ranking, it is possible to identify the variables that have the strongest association with the target variable. In the Decision Tree model, it was found that current asset has the highest predictive weightage tendency of thinking about retirement, followed by current income. It can be suggested that mental accounting allocation on the tendency of thinking about retirement is weighted most by total current asset, total annual current income, and total future income for wealth allocation. Meanwhile, expenditure is on discretionary items, necessities items, and luxury items accordingly.

From a demographic perspective, it is observed that Bumiputras generally have a higher predictability of thinking about retirement, followed by Chinese. Meanwhile, marital status has a higher weightage than household and education size. Being female would entail a higher predictability in thinking about retirement than females.

4.6.6 Random Forest

The Random Forest model that predicts tendency of thinking about retirement performed with accuracy reaching 58.60%, where AUC achieved 54.50%, precision reaching 80.30%, recall at 67.90% and F measure at 69.00%. In this regard, Random Forest is a good model that can be used to predict tendency of thinking about retirement. A single decision tree within the Random Forest model is presented as below, as the whole Random Forest is made up of 60 trees which may not be viable to presented in this study:

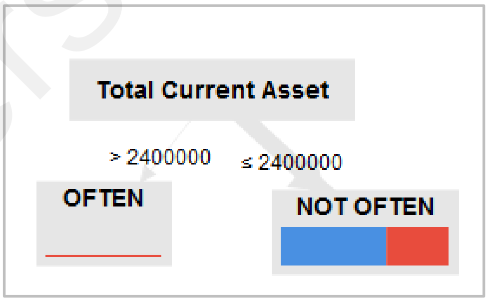


Figure 4.7: Single Decision Tree from Random Forest Model for Predicting Tendency of Thinking About Retirement

The small number of branches could be owed to possibility of the data set being imbalanced and complex to predict. In this case, for each modelling algorithm, predicting the class of interest (often think about retirement) will be the best choice. Therefore, having imbalanced data is not necessarily a problem, as balancing the data before running the model would not give a perfect model for deployment. It remains important that validation of models is done on the original (imbalanced) distribution even when using some sampling method to build better models.

In such cases, it becomes pertinent to explore alternative methods to assess the importance or significance of the predictor which brings to the RapidMiner's independent variable importance ranking, which allows for the understanding of which variable contributing the most to the model's predictions. By examining this ranking, it is possible to identify the variables that have the strongest association with the target variable. In the Random Forest model, it was found that current asset has the highest predictive weightage to tendency of thinking about retirement, followed by current income. It can be suggested that mental accounting allocation on tendency of thinking about retirement is weighted most by total current asset, total annual current income, and total future income for wealth allocation. Meanwhile, expenditure is on discretionary items, luxury items, and necessities items accordingly.

From a demographic perspective, it is observed that Indians generally have a higher predictability on thinking about retirement, followed by Bumiputera. Meanwhile, education has a higher weightage than marital status and household size. Being male would entail a higher probability of thinking about retirement than females. For the Random Forest model, the rest of the features are below 0.000, which signals low weightage in predicting retirement satisfaction.

4.6.7 Gradient Boosted Trees

The Gradient Boosted Trees model that predicts retirement satisfaction performed with accuracy reaching 80.30%, where AUC achieved 47.80%, precision reaching 80.30%, recall at 100% and F measure at 89.10%. In this regard, Gradient Boosted Trees can be used to predict retirement satisfaction. For this model, the model for a single tree within the whole Gradient Boosted Trees which is made up of 90 trees may not be viable to presented in this study, as a single tree exhibited an average of 40 branches each. In this regard, there may be risk of overfitting of the model, given the large number of branches for each tree and the large number of trees that make up the Gradient Boosted Trees.

In the Gradient Boosted Trees model, it was found that current income has the highest predictive weightage on tendency of thinking about retirement, followed by current asset. It can be suggested that mental accounting allocation ton tendency of thinking about retirement is weighted most by total current income, total annual current asset, and total future income for wealth allocation. Meanwhile, expenditure is on luxury items, necessities items, discretionary items, accordingly.

From a demographic perspective, it is observed that Bumiputras generally have a higher probability of satisfaction in retirement, followed by Indians. Meanwhile, household has a higher weightage than marital status and education size. Being male would entail a higher probability of being satisfied in retirement than females. For the Gradient Boosted Trees model, the rest of the features are below 0.000, which signals low weightage in predicting tendency of thinking about retirement.

4.7 Analysis of Tendency of Thinking about Retirement vis-à-vis Retirement Satisfaction

Upon assessment of all the models, it is suggested that the ANN is the most suitable model for predicting tendency of thinking about retirement. This is as standard statistical analysis such as logistic regression could not model tendency of thinking about retirement due to its low R-square measurement which relates to lack of goodness of fit of the models. This entails the models' inability to model tendency of thinking about retirement. However, this should not be taken as a signal that there is no relationship between independent variables and dependent variable. In this regard, machine leaning models are used as an on-par alternative to standard statistical analysis (Garibay et al, 2022). However, other machine learning models such as Naïve Bayesian, Decision Tree, Random Forest, and Gradient Boosted Trees had weaknesses which was not observed in ANN such as independence assumption, small number of branches and risk of overfitting, which could influence predictive outcome, and low accuracy rate. As such, the outcome for the ANN model developed is referred to for this study to answer objective 3. With the exception of Naïve Bayesian and Gradient Boosted Trees model, it was observed that current asset held most predictive power on tendency of thinking about retirement for wealth component of mental accounting categories. Meanwhile, discretionary items held most predictive power on tendency of thinking about retirement for Generalised Linear Model, ANN model, Decision Tree model, and Random Forest model.

Similar performance is observed across all models' performance metrics as the data set is imbalanced and complex to predict. In this case, for each modelling algorithm, predicting that the majority class (often thinking about retirement) will be the best choice. Therefore, having imbalanced data is not necessarily a problem, as balancing the data before running the model would not give a perfect model for deployment. It remains important that validation of models is done on the original (imbalanced) distribution even when using some sampling method to build better models. Even with a mindset that frequently thinks about retirement, a change of mental accounting behaviour is needed to ensure retirement satisfaction.

In comparison to the ranking of items that represent the best allocation that leads to retirement satisfaction, which is represented by the predictive power of mental accounting categories that brings retirement satisfaction as discussed in section 4.4 Machine Learning Model Outcome for Predicting Retirees' Retirement Satisfaction, a change of behaviour would need to occur to get an individual who is thinking about retirement to rearrange wealth allocation from putting most weightage on the current asset, current income, and future income respectively to the future income, current income, and current asset respectively in order to become satisfied in retirement. In this regard, this study confirms Hypothesis 3, where a re-arrangement of mental accounting categories for those thinking about retirement towards the best mental accounting allocation to enhance retirement preparedness. In figure 4.3, blue boxes are the wealth categories of mental accounting while green boxes are the expenditure categories of mental accounting.

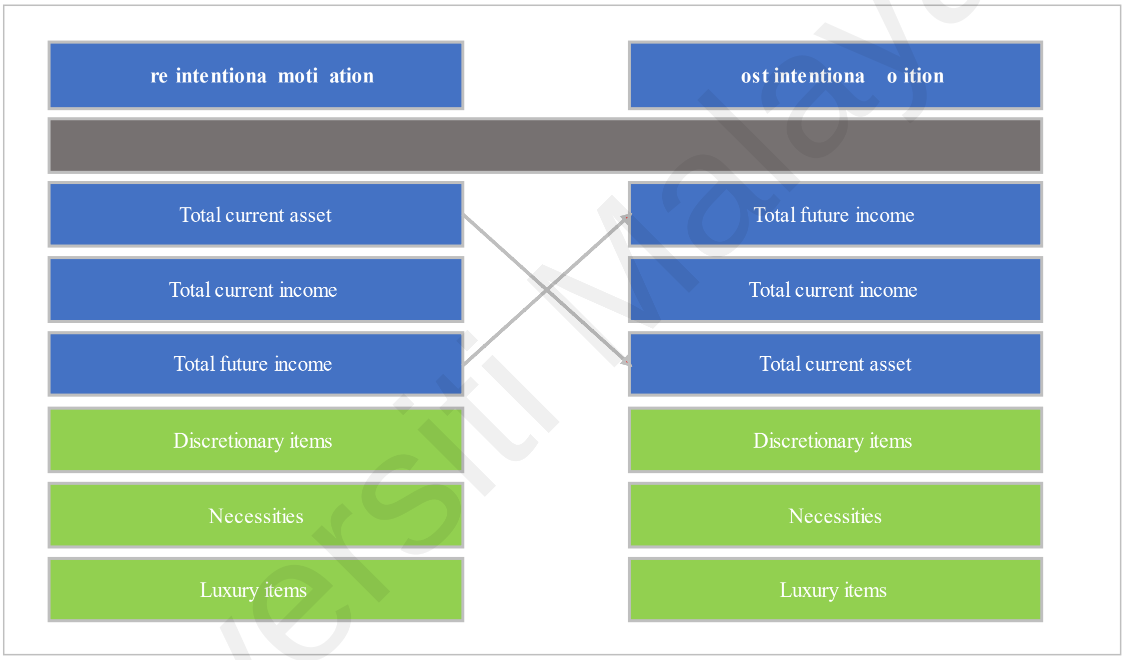


Figure 4.8: Mismatch of mental accounting allocation between pre-retirees who often think about retirement and retirees who have achieved satisfaction in retirement.

Towards being more prepared for retirement, pre-retirees are encouraged to move from heavily saving in current assets such as in fixed deposits (which has the highest predictive weightage on the tendency of thinking about retirement based on an ANN model with an accuracy rate of 65.80%) towards more savings in future income (which has the highest predictive weightage on retirement satisfaction based on an ANN model with an accuracy rate of 80.33%) such as in Private Retirement Schemes (PRS). Here, the results from objective two spells out the best mental accounting ranking that should be the final aim for pre-retirees in preparing themselves for retirement. With this information in hand, financial literacy that is informed by behavioural economics considerations becomes more pertinent. This is as the arrangement of mental accounting categories for those who regularly think about retirement may not be the best towards achieving retirement satisfaction. To ensure pre-retirees become prepared for retirement, they must be aware that putting the most effort into accumulating current assets may not give way to retirement satisfaction. Instead, they must focus on ensuring that their future income is sufficient and able to provide for them in retirement. In this way, they will have a higher probability of achieving retirement satisfaction. To reiterate, current income includes the sum of pension, rental income, salary/income from the business, insurance, allowances from Social Security Organisation (SOCSO), Social Welfare Department (Elderly/Disability aid), Zakat/donation received, dividend from shares or unit trusts, subsidies/cost of living allowance (Bantuan Sara Hidup), allowance or contribution from Armed Forces Fund Board (LTAT), net intergenerational transfers and others combined in Ringgit Malaysia.

Current assets refer to the sum of home equity, land, other properties, business shares, insurance, bank savings (fixed deposit, savings/current account) and others combined in Ringgit Malaysia. While future income refers to the sum of Employees Provident Fund (EPF) savings etc.), properties, Tabung Haji (Islamic Pilgrimage Fund), Unit trust/ASNB/endowment, shares, private retirement schemes and others combined in Ringgit Malaysia. These mirror the items within the wealth categories as in Schooley and Worden (2008).

In this regard, pre-retirees can best prepare themselves for retirement by converting their current asset to future income wealth categories. For instance, transferring bank savings to their Employees Provident Fund (EPF) savings, Tabung Haji (Islamic Pilgrimage Fund), Unit trust/ASNB/endowment, shares, or private retirement schemes (PRS).

Financial planners would benefit from this finding as they could provide guidance to pre-retirees on how best to balance asset accumulation without forgoing the importance of future income, as savings geared exclusively for retirement would have the most weightage for retirement satisfaction.

CHAPTER 5 : CONCLUSION

5.1 Introduction

In one retiree category, they may focus more on the perceived gain over the perceived loss. In another pre-retiree group, they may exhibit loss aversion. All these points to the uneven weightage respondents put on non-monetary perceived gain and perceived loss. This confirms and adds to previous literature where individuals are known to exhibit non-monetary mental accounting (Huang et al., 2020; Kahneman & Tversky, 1979; Shefrin & Thaler, 1988; Townsend, 2018; Yeh, 2020). With this knowledge in hand, it is beneficial to include a more in-depth focus on behavioural finance, given that it permeates the decision-making space in individuals. Currently, the focus on behavioural finance in Malaysian financial planning training modules remains limited, especially on in-depth discussion on the presence of mental accounting and its impact on financial decision-making.

While it is clear that individuals, by and large, exhibit mental accounting behaviour, it is also pertinent to examine the predictive weightage mental accounting has on retirement satisfaction to understand the predictive weightage each wealth and expenditure mental accounting categories have on retirement satisfaction via the ANN model. On this note, it is demonstrated that future income has the most predictive weightage on retirement satisfaction. Additionally, it was found that expenditure on discretionary items has the most predictive weightage on retirement satisfaction in comparison to other expenditure categories, such as necessities and luxury items. This is natural; seeming that future income should stick true to its intention of being the main source of income in retirement, while expenditure on discretionary items would bring more satisfaction for individuals when compared to expenditure on necessities.

Riding on this finding, a comparison of the ANN model results for mental accounting attributes on retirement satisfaction and tendency to think about retirement is conducted to understand how best ranking of mental accounting categories can bring about better preparation for retirement. Regressively, a separate ANN model was also developed to understand the predictive weightage of wealth and expenditure mental accounting categories have on the tendency to think about retirement.

From here, it was found that the current asset has the most predictive weightage among all wealth categories on the tendency of thinking about retirement, while the discretionary item has the most predictive weightage among all expenditure mental accounting categories. In essence, a narrower focus is given to individuals who often think about retirement and how they rank the importance of each wealth category. Next, the ranking of wealth categories for those who think about retirement is compared with the ranking of wealth categories that may bring the most satisfaction in retirement. It is understood that for those who often think about retirement, there is a need to inculcate a change of behaviour towards a better mental accounting behaviour (i.e., re-arranging their wealth mental accounting category from having the most weight on the current asset to having most weight on future income). The strategy is encouraged to ensure better preparation for retirement. Towards the end goal of being prepared for retirement, an individual may consider converting their current asset to future income wealth categories. For instance, transferring bank savings to their Employees Provident Fund (EPF) savings, Tabung Haji (Islamic Pilgrimage Fund), Unit trust/ASNB/endowment, shares, or private retirement schemes (PRS). On this note, it is clear that with better mental accounting behaviour, better financial management and a better level of preparation for retirement are expected, as suggested by previous literature (Lim et al., 2021; Mahapatra & Mishra, 2020; PIDM, 2021).

5.2 Concluding Remarks

So far, throughout the study, the importance of the behavioural aspect in financial decision-making has been highlighted by first determining whether mental accounting does, in fact, occur in respondents. It was found that a majority of respondents from both retirees and pre-retirees exhibit this behaviour, as these respondents are suggested to view perceived non-monetary gains and losses differently. Pursuant to this finding, it became clear that the next step was to examine mental accounting categories (i.e., in the form of current income, current asset, future income, necessities, discretionary items and luxury items) that have predictive weightage on achieving retirement satisfaction. In hindsight, it was natural for wealth and expenditure to have predictive weightage on retirement satisfaction. However, it was not as clear how the categories within wealth and expenditure groups respectively would impact retirement satisfaction. In this regard, it was found that mental accounting categories do, in fact, have predictive weightage on retirement satisfaction. It was demonstrated that future income (i.e., stream of income designed towards providing financial resources in retirement) has the most predictive weightage on retirement satisfaction. Clearly, having a strong financial resource is important for an individual to be satisfied in retirement.

Following this finding, a deeper look at the predictive weightage of mental accounting categories on the tendency for thinking about retirement is conducted, towards being satisfied in retirement. The findings from this analysis are then compared to the previous findings on the predictive weightage of mental accounting categories on retirement satisfaction. It was found that current assets had the most predictive weightage on the tendency to think about retirement.

In essence, this study spells out the discrepancy in terms of the most important mental accounting category between respondents who often think about retirement and respondents who have achieved retirement satisfaction. It was found that those who often think about retirement had current assets with the highest predictive weightage, while those who have achieved retirement satisfaction had future income with the highest predictive weightage. It is recommended that it would be beneficial for individuals to move from putting more importance or weightage on current assets towards putting more importance or weightage on future income to be more prepared for retirement. Through best ranking and savings in different mental accounting categories, an individual can be prepared for retirement better with having satisfaction in retirement as the targeted outcome. The findings further underscore Sunstein (2021)'s work where it was argued that once algorithms from machine learning are deployed, it can greatly reduce bias in modelling outcomes of the analysis. Consistently, machine learning procedures can provide a robust, efficient, and effective analytic method (Heo et al., 2020) where achievement of retirement satisfaction can be improved from the machine learning analysis's results. In addition, the complementarity relationship between machine learning and behavioural economics is that behavioural economics provide testable hypotheses which help explain observed patterns of behaviour where machine learning describe patterns in behavioural data consistent with Heal et al (2022) is demonstrated throughout this study.

5.3 Implications of the Study

This study has demonstrated that behavioural factors matter in the study on retirement and decision-making. While this study remained consistent with the theory that wealth and expenditure do, in fact, control the outcome of satisfaction in retirement, it expands previous understanding of where mental accounting categories have different predictive clout on the outcome of retirement satisfaction. A deeper understanding of the impact of mental accounting categories on those who often think about retirement and whether it can translate to achieving retirement satisfaction is vital, as the findings from this can necessitate a guide towards becoming prepared for retirement, especially for pre-retirees. For policy-making, it opens a new understanding of where individuals, in general, behave in a certain systematic way which can be leveraged to encourage towards being better prepared for retirement. Mental accounting behaviour presents an opportunity for government and stakeholders to relook at current policies which assume wealth and expenditure to be fungible. In particular, the importance of the future income category should be focused on where it would benefit individuals to invest more towards the accumulation of future income. Meanwhile, financial product developers can also move from focusing on the mere accumulation of wealth to focusing on a suite of financial products that feed into the mental accounting category of future income. Meanwhile, training for financial planners can also be realigned to ensure that the accumulation of current assets for an individual must also be balanced with accumulation in the future income category.

The usage of machine learning opens a new backdrop for future studies relating to retirement where behaviour can be understood better, given that several assumptions normally assumed when using standard statistical analysis can be relaxed or abandoned altogether. While it remains important that standard statistical tools and machine learning are treated as complementary methods in social science, it is pertinent that the study on retirement preparedness be augmented with the usage of machine learning, given that it can detect behaviour and is also shown to be able to predict behaviour.

5.4 Policy Responses

In this section, this study discusses the implication stemming from the results above and the policy recommendations. In general, it is clear that Malaysians, by and large, are mostly not financially equipped for retirement. This study indicates that while this might be the case, a refined approach towards understanding retirement preparedness from the lens of behavioural economics may be beneficial with the usage of machine learning methods. In essence, how individuals allocate their wealth across mentally established non-fungible categories can predict the satisfaction they feel in retirement. In fact, how much they think about retirement can also be predicted by how these individuals allocate their wealth across the said categories.

This is a gap from previous findings where education material and awareness campaigns approach the masses in general with the notion that all types of wealth are equal and fungible, therefore, advocating for the accumulation of wealth regardless of type towards preparing for retirement. While this might be partially true, it is also pertinent to note that education materials and awareness campaigns must take into consideration that individuals do not see all types of wealth as equal and fungible. Therefore, a more in-depth discussion on the predictive impact mental accounting has on retirement preparedness must take place to better engage Malaysians. The finding that individuals who often think about retirement fail to allocate and arrange their wealth according to the ranking of wealth types that can apparently bring the most satisfaction in retirement should be a concern to relevant parties to ensure that this gap is addressed accordingly.

Notwithstanding that, while some topics, such as basic management of finances, should be covered in education materials and awareness campaigns, the focus should also be given to retirement preparedness gaps that are born from established and observed behavioural patterns such as mental accounting. A full understanding of these topics will enable them to better manage their finances and grow their assets in preparing them for their grey years.

Moreover, a review of the current structures available for retirement savings must take place to suit the idea that individuals have behavioural tendencies that may not run consistent with traditional or mainstream economic assumptions and considerations. The government may consider having a matching benefit for retirement savings to incentivise Malaysians to save in the proper channel for their retirement, as this will form their future income. Similar to the Youth Incentive allocated for Private Retirement Schemes, which expired in 2018, the government could re-introduce and re-purpose the incentive on a wider scale to cover all Malaysians. Aside from that, the tax break for Private Retirement Schemes (PRS) and Employee Provident Funds (EPF) should also be continued to incentivise people to save up for their retirement. Separately, the focus should be given to those who are at the peak of their careers and nearing retirement years, as it becomes very crucial for them to save for retirement at this stage of their lives.

For those about to retire, a further dis-incentivisation is also needed for investments into current assets such as home equity, land, other properties, shares of the business, insurance, bank savings (fixed deposit, savings/ current account) which can be shifted towards investments in Employees Provident Fund (EPF) savings etc.), properties, Tabung Haji (Islamic Pilgrimage Fund), Unit trust/ASNB/endowment, shares, private retirement schemes.

As a method in moving toward better mental accounting, this study suggests a gradual process in the form of a gliding path in terms of percentages (similar and in fashion with target date funds) allocated from current asset to future income mental accounting category, which can ensure a smoother transition for an individual heading towards retirement. For example, at 40 years of age, an individual could split 60% of their wealth into their current asset mental accounting category while another 40% goes to the future income mental accounting category. At 50 years of age, the ratio could be tipped to 50:50, towards 40:60 by 60 years of age and finally to 30:70 at 70 years of age onwards. In this manner, the transition towards retirement may be smooth and easy for individuals where both mental accounting wealth categories are still maintained but in different proportions.

Moreover, financial advisors and planners may also benefit from reflecting this suggestion in financial plans provided to their clients, where an all-encompassing platform that can transfer from one type of wealth to another with a user-friendly interface can be explored as a way to make the transition to retirement convenient and smooth. All this will naturally lead towards better preparation for retirement. Moreover, digital investment managers could include nudges in the form of prompts to users to escalate their wealth from one mental accounting category to another. Naturally, it would benefit both investors and investment companies alike if a platform that maps out mental accounting categories in an investment app could enable investors to view their wealth allocation and invest or transfer portions of their wealth to different mental accounting categories accordingly. This will enable individuals to take advantage of their mental accounting behaviour and plan their finances for retirement better.

From a demographic perspective, it was observed that Indians have more tendency to think about retirement than Chinese and Bumiputera accordingly. However, it is observed that Bumiputras generally have a highest probability of satisfaction in retirement, followed by Chinese and Indians. It remains pertinent to encourage higher retirement savings across the board. However, special consideration should be given to pre-retirees from the Bumiputera community, seeming that while they often think less about retirement, they were found to likely be satisfied in retirement. This finding leads to multipronged points. One, there is a need to educate members of the community to take advantage of the effort in thinking about retirement often to be more proactive in wealth accumulation via retirement savings. Secondly, there is a need to educate members of society on the variety and importance of each type of resource needed in retirement. Preparing for retirement requires the ability to have adequate financial, social, psychological and health resources (Noone et al., 2013). Here, Bumiputera were found to be likely to think less about retirement often but were most likely to feel satisfied in retirement. While intuitively positive, there is a need to encourage members of the Bumiputera community to think more about retirement and re-assess the resources they have and need for retirement.

From a gender lens, females tend to think more about retirement, and those females may exhibit higher satisfaction in retirement. The implication for males is that they are not only likely to think less about retirement but may also feel less satisfied in retirement. In this regard, a deeper study is encouraged with a special focus on males. In this regard, it is pertinent to pivot towards understanding their role in society and their struggles in preparing themselves for retirement.

5.5 Limitations and Recommendations of Study

The empirical results reported herein should be considered in light of some limitations. Firstly, the limitation of this study is that the age of respondents is constrained to be 40 years old and above. Moving forward, other researchers are invited to study retirement preparedness from a cohort perspective as this this study assumes that behaviour of pre-retirees and retirees are consistent, given that each cohort displays different spending and savings trends. This is important given the global trend of the ageing of society where successive generations will become the biggest generation in terms of population size when they become the oldest generation in a country.

Separately, only the first wave of the MARS data was available at the time of the study, whereas the second wave of data collection was disrupted due to the health crisis. While causality can only be determined via longitudinal data, correlation is sufficient in this study. In moving forward, the study's findings on the best-performing model can be scored using the second-wave data to further understand the relationship between the dependent and independent variables in this study. Additionally, another limitation of this study is as assets are reported on an individual basis in the MARS survey. This departs the general perception that assets are jointly owned by married couples. In addition, the style and structure of the questionnaires and the answer option was not perfectly suited for analysis where certain liberties were taken in using the outcome from the survey to fully take advantage of the quality of information from the survey.

From a methodological view, some machine learning techniques, models, and algorithms have optimal prediction levels yet low interpretability levels. However, the main aim of this study remains prediction performance of models. Moving forward, it is recommended that a comparative analysis be conducted to compare the performance between standard statistical analysis and a wider range of machine learning models to enhance understanding of relationships that define retirement preparedness. Further, examining conditional probabilities instead of just frequencies of those who report satisfaction or frequency of thinking about retirement where a contingency table could be constructed is included as another future research direction which can also be supported with a more robust measurement of perceived gains and loss. One possible recommendation for future research would be to facilitate a personalized and dynamic approach to retirement planning, as they can adapt to individual characteristics and preferences. Further, the study By leveraging machine learning algorithms, the study can develop personalized models that consider individual mental accounting attributes and provide tailored recommendations for improving retirement preparedness.

Savings behaviour is captured via the difference between yearly wealth minus yearly expenses, where a surplus would indicate the individual's positive savings behaviour. This is a limitation of the study as the surplus may not be conclusively known to be formally saved and become part of savings for retirement. Secondly, EPF's Belanjawanku annual income amount for elderlies in Klang Valley was used to calculate the adequate amount of savings needed for retirement, which is the study's reference amount for savings adequacy. While most Malaysians reside in urban areas with living standards comparable to Klang Valley, which makes the amount suitable for this study, the actual annual income amount for elderlies in other parts beyond Klang Valley may deviate from the reference amount as the cost of living in other parts of the country whether urban or rural may be different. In moving forward, this study can be replicated on Belanjawanku information in other states. Lastly, the measure of retirement preparedness, while contextualised in terms of those in retirement and those who have yet to retire, the combination of subjective and objective retirement preparedness elements in this variable remains limited where more elements can be adapted from Aegon's Retirement Readiness Index for the Malaysian scenario. Researchers are invited to enhance future research endeavours by considering including more elements in understanding retirement preparedness.

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