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Predicting savings adequacy using machine learning: A behavioural economics approach

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ABSTRACT

This paper proposes a machine-learning-based method that can predict individuals' savings adequacy in the presence of mental accounting. The proposed predictive model perceives wealth and consumption, each of which is being divided into three non-fungible distinct classes. The predictive model has found that the mental accounting categories have predictive power on savings adequacy, whereby the emphasis is that the expenditure on luxury items is followed by the total current asset. Savings adequacy is best predicted by the decision tree model based on the Malaysian Ageing and Retirement (MARS) survey data. Surprisingly, it was found that future income and necessities had a lower predictive power on savings adequacy. The findings suggests that individuals, financial professionals, and policymakers should be cognizant that higher likelihood of achieving savings adequacy can be achieved by focusing on accumulation of current asset while lowering expenditure on luxury items.

1. Introduction

The issue of savings adequacy has always been part of the ongoing discussion on social protection policies alongside coverage and the cost of social protection provision. Worldwide, countries are pushing towards eliminating poverty, and it remains imperative that ideal living standards are achieved within limited government fiscal capabilities. As such, the promotion of achieving adequacy should also come from fellow individuals where policies should be crafted towards encouraging individuals to save enough reserves to finance their consumption in later years. The inclusion of individuals should be part of the more extensive conversation on protection against financial risks, prevention against reduced financial well-being levels, and promoting of good living standards for individuals.

Among the challenges, Malaysians also face an inadequate amount of financial capability to prepare against financial 'shocks' such as job loss or facing illnesses. Moreover, most Malaysians are unaware of the benefits of subscribing to insurance policies. All this would naturally point to the weak level of capability of Malaysians to save.

While the savings rate among Malaysians has been historically on the low side (Khazanah Research Institute, 2020), the COVID-19 pandemic has brought new concerns given the contraction of global economic growth and the rising unemployment rate. The impact of COVID-19 on Malaysians is compounded with a finding in a recent survey by the Department of Statistics Malaysia (DOSM), where most working Malaysians have savings equivalent to less than 2–4 months' worth of their monthly salary (Goh, 2020). This goes against the recommended rule of thumb by financial planners, which encourages an individual to have at least 3–6 months' worth of a monthly salary in preparation of emergency or financial shocks (Anong & DeVaney, 2010). This fact brings forth a more relevant need for policymakers to re-assess factors that contribute towards adequate savings for Malaysians.

Against this backdrop, the current paper proposes a machine-learning-based method to understand how different wealth and consumption categories are framed under mental accounting bias effect savings adequacy (i.e., among the individuals' savings decision-making), which relatively would be a more relevant objective considering the current economic challenges that are faced by Malaysians. While the relationships between income, expenditure and household savings have been shown, the influence of mental accounting is not clear from previous studies. A deeper look into how mental accounting influences savings adequacy is one of the key objectives in this study.

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Financial counselling and planning professionals, as well as policy-makers, have a stake to better understand the factors that influence a person's saving adequacy. Correspondingly, the research questions for this study include:

- Do mental accounting categories have predictive power on savings adequacy?
- How does mental accounting categories influence savings adequacy?

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 basis in behavioural economics can be used to systematically show and suggest factors that impact a person's savings adequacy- in a wholesome and complete fashion, it may be possible to design a system of savings that improves the level of savings among Malaysians (Fig. 1).

2. Review on existing literature

2.1. Factors influencing savings adequacy

In the 2016 study on Dutch households, factors such as demographics, income, skills, and education, including financial literacy are known to be the factors that influence savings behaviour which impacts adequacy (Brounen et al., 2016). The inclusion of the financial literacy element runs consistent with a finding by Lusardi in 2008 as financial literacy is increasingly becoming an important topic in studies related to savings (Gallego-Losada et al, 2022). Globally, it is observed that low-income households generally have low savings. This observation can be attributed to the fact that the net disposable income for low-income households is low, and that the received income is generally spent on necessity, goods, and services. Financial literacy is also found to affect the savings behaviour in university students; those who are aware of the compounding nature of interest rates are more likely to have positive savings habits (Foltice & Langer, 2018). Separately, the belief in one's financial knowledge that is not reflected on actual financial literacy levels also has implications on the savings level. Accordingly, it has been found that those with financial knowledge overconfidence are more likely to make an early withdrawal to support current consumption, thereby lowering the savings amount (Lee & Hanna, 2020) (Fig. 2).

In Malaysia, it is noted that the rate of savings has been low, especially for retirement. The typical factors that influence savings behaviour in Malaysia include services quality, religious belief, and knowledge (Ismail, Khairuddin, Alias, Loon-Koe, & Othman, 2018). 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 need comes at a time when savings are difficult due to the high cost of living and slow growth of income (Malaysian Financial Planning Council, 2020). In essence, multiple factors impact savings for a developing country such as Malaysia. It remains pertinent to include behavioural elements along with economic elements in investigating how these elements play a simultaneous role to influence savings decisions and levels in Malaysia (Fig. 3).

2.2. Measurement of savings adequacy

In this study, the discussion on savings adequacy adopts a micro-scale perspective, i.e., the point of view of an individual person. Savings adequacy is usually defined as the amount of wealth that is sufficient to sustain a person's consumption in his or her retirement years. Having an adequate amount of savings will naturally render one as financially prepared for retirement. 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 the individual or household needs as a guide to prevent poverty. Globally, the international poverty line was set at USD1.90 a day as of 2015, where on average this amount is considered sufficient for the 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 across time (Ferreira et al., 2016). While this measurement has been derived based on the average poverty line across 15 low-income countries, many countries have established their own poverty line which reflects the nuances of their respective economic reality.

In the United States, the measurement of poverty is divided into two distinct measurements. In one, the figures of poverty threshold are provided by the Census Bureau and are used for statistical purposes. The figures range from USD13,465 to USD50,035, depending on the

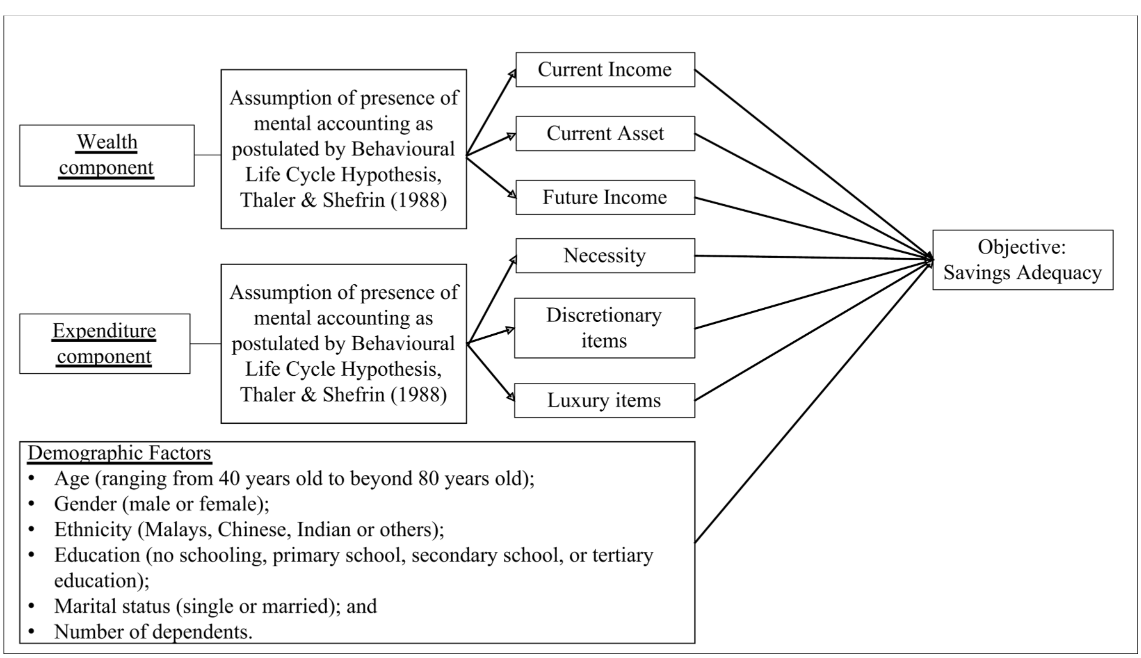

Fig. 1. Conceptual Framework.

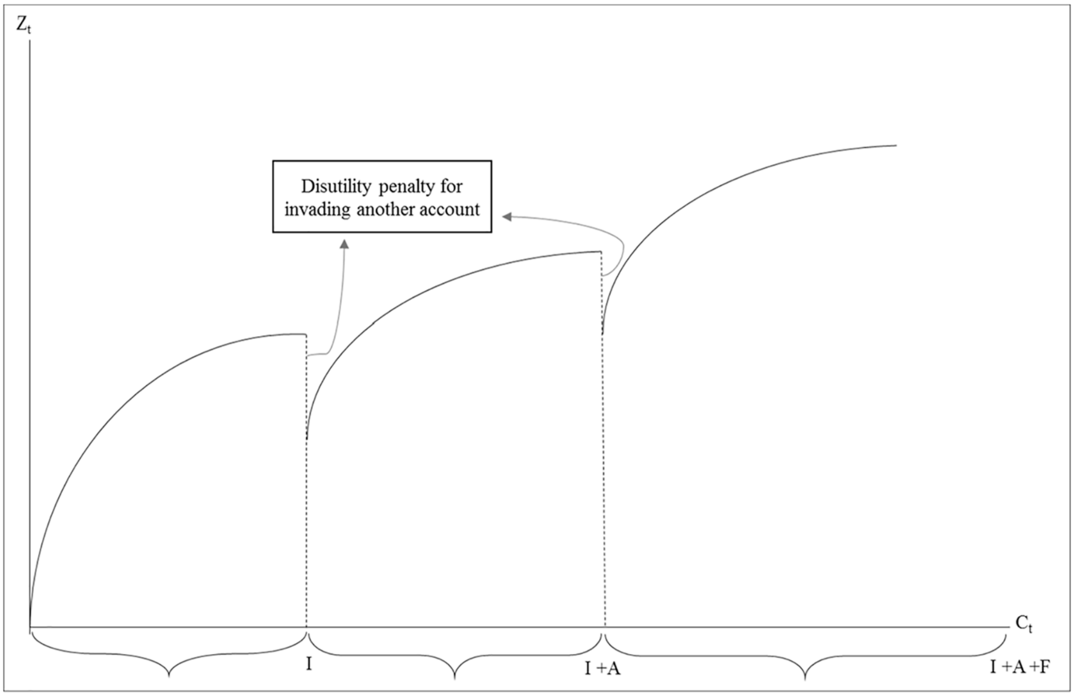

Fig. 2. Concave Utility for Mental accounting.

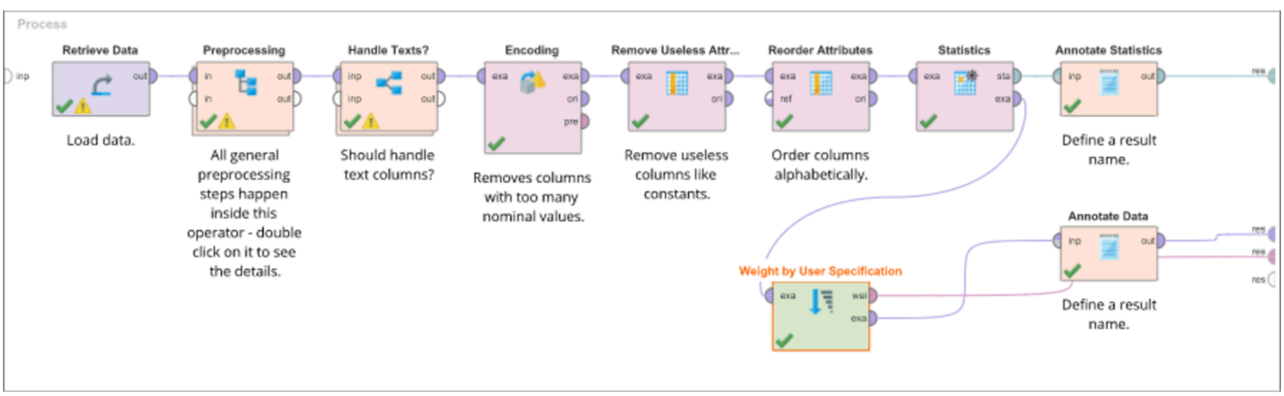

Fig. 3. Modelling Flow Chart.

household head's age and the household's size (US Census Bureau, 2021). Correspondingly, another set of measurements is more in-depth, where the figures are adapted to suit the economy of the different states within the United States. The second set of measurement was crafted generally for administrative purposes. In Malaysia, the minimum poverty line was set at RM2,208 (Department of Statistics Malaysia

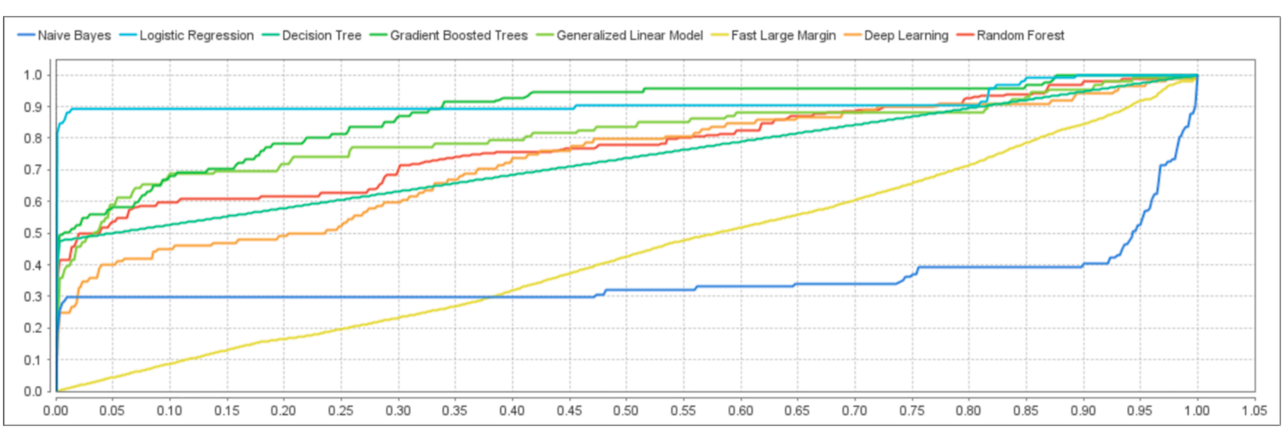

Fig. 4. Receiver Operating Curve (ROC).

[DOSM], 2020) (Fig. 4).

It is thought that if a person has enough savings 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.

While the recommended amounts by the governments are useful to a certain extent, it does not consider the factors necessary for individuals to live meaningful lives, which includes the financial capability to be full participants in society and economy where the needed amount 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 countries' 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 the member states. Additionally, with these considerations in mind, several organisations have considered setting another set of thresholds that is 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. Table 1 encapsulates information from a few organisations which have introduced recommended amount of wealth that Malaysian citizens should have to sustain their livelihood.

With regard to having a benchmark to indicate savings sufficiency, governmental organisations have also recommended replacement rates to ensure that consumption can be smoothened throughout the person's lifetime. Generally, savings are adequate should they be able to replace a portion of a person's salary. The salary can be a person's last drawn salary or the career's average salary. A well-known replacement rate that is recommended by financial planning experts is usually 70%–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 3–6 months' worth of a monthly salary in preparation for an emergency or financial shocks (Anong & DeVaney, 2010). Another minimum recommended amount by EPF for its members to have upon retirement is RM240,000. This amount is based on the minimum monthly pension payment calculation 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).

Table 1
Information Summary of Adequacy Measures.

Organisation	Details	Recommended Amount
Employee 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.	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 the basket of goods and services prices needed to sustain their livelihood.	RM4,500 monthly (or RM 54,000 annually)
Wage Indicator Foundation	In 2019, it released a recommended amount for a typical Malaysian family (i.e., two adults and number of children based on Malaysia's fertility rate in 2010 to 2014).	RM 1,419 to RM2,053 monthly (or RM17,028 to RM24,636 annually)

While heuristics are 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 and Marcinkiewicz (2015), the replacement rates (thumb rules) used was found to be unreliable to be a guide towards having savings adequacy. The heterogeneity of what constitutes adequacy to individuals has led to the findings by Chybalski and Marcinkiewicz (2015). 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).

2.3. Mental accounting concept

In the review of frameworks that are proposed in the past relating to income, consumption and savings, the expanded version of Life Cycle theory which is the Behavioural Life Cycle Theory that is developed by Thaler and Shefrin in 1988, in which the mental accounting concept is conceived, is based upon as the framework for this study.

In the traditional Life Cycle model setting, an individual is assumed to have a constant marginal utility where savings are a measure to delay the consumption of wealth to a later time in order to maintain the same level of utility throughout the individual's lifetime. With each successive generation, wealth accumulation rate has grown and resulted in intergenerational wealth transfers from parent to children. The Behavioural Life Cycle Theory was developed at a time when behavioural economists argued that humans found it difficult to estimate their life-cycle wealth, longevity, and future spending needs because humans struggled to reconcile the desirability of saving when the income was high, with a stronger temptation to spend (Statman, 2017). This also follows the weak support for the Life Cycle Hypothesis and a 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, Skinner and Weinberg in 2001, where decisions are made in relation to retirement wealth and savings that are more in line with the perceived 'rule of thumb', 'heuristics', and 'mental accounting', rather than the expectation of complete rationality from the agents.

In the Behavioural Life Cycle, behavioural elements such as self-control, mental accounting and framing are inculcated in the Traditional Life Cycle Hypothesis. The assumptions about this hypothesis are that households treat components of their wealth as non-transferable (non-fungible). Wealth is therefore not easily interchangeable with other types of wealth, even in the absence of credit rationing. This departs from the traditional Life Cycle Hypothesis which assumes one type of wealth throughout a person's lifetime.

Wealth is framed into three subcategories, i.e., current income (such as cash, checking accounts, money market accounts) current assets (such as savings account, unit trust funds, other capital market products) and future income (such as home equity and retirement savings) (Schooley & Worden, 2008). The mental framing of wealth is done to manage the difficulty the agents face in managing their finances to avoid the risk of running out of money before their eventual death (Statman, 2017). The current income of a person faces the highest temptation to be used with the future income facing the least temptation.

2.3.1. Conceptual framework

Against the backdrop, the conceptual framework for this study is thus summarised as follows:

In this hypothesis, 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 a higher self-control. An example of self-control is the cost of forgoing an immediate spending to save for future consumption. Mental accounting simply means a person would find one type of wealth is 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. This is done generally to reduce cognitive burden on financial decision making (Zhang & Sussman, 2018). Framing is the saving rate that can be affected by the way in which increments to wealth is framed. For example, an increase in regular income is treated differently than an anticipated bonus.

As consumption increase, utility increase at a diminishing rate. This in turn also means that willpower decreases. Once 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. As using the balance in the current asset account, A is less tempting that 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 for when the balance in A is depleted and the individual invades the final account, future income account, F.

2.4. Advantages of machine learning in economic research

In line with the evolution in economic research, machine learning methods are increasingly being used for prediction, categorisation, and causal inference together with assessing the impact of an event or the implemented economic policies (Athey, 2019). As a technique, it remains a useful method for further economic empirical analysis since it opens the way towards understanding new relationships between variables.

Machine learning has several advantages over econometrics where for the economists, the selection and design of economic and empirical models are largely data driven (known as auto-modelling). In building a machine learning model, the main goal is to predict, describe, and or explain some social phenomenon. This signals the researchers' main task to identify the model that best accomplishes this goal, under some definition of the best, whereby a principle-based, systematic, and strategic approach allows for better performance of the models as the researchers can fully describe the process of model selection through 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 the models since 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 traditional constraints that are related to interaction or compounding effects, or multicollinearity (Heo et al., 2020). Further, there have been developments within the machine learning field that can tackle more complex research problem with multi-objective optimisation problems that require advanced solutions (Ma et al, 2021).

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

Given the proliferation of technology that is used 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 the existing econometrics methods (Charpentier, Flachaire & Ly, 2018; Garbero & Letta, 2022) to enhance the understanding of established relationships in the field of economics, especially in behavioural economics (Sunstein, 2021). This is further substantiated by Sunstein (2021) where it has been argued that once the algorithms from machine learning are deployed, it can greatly reduce the bias in the analysis of the modelling outcomes. When an educator, researcher, financial service professional, lender, or policy maker needs to describe and or predict a household's future financial situation, it is found that the machine learning procedures can provide a robust, efficient, and effective analytic method (Heo et al., 2020).

Given the machine learnings ability to analyse the large amounts of data, a machine learning technique will far outperform the traditional linear 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 is 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 the 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 studies that are related to finance, a novel approach of comparing multiple machine learning models is to predict bank insolvencies (Petropoulos et al., 2020).

3. Methodology

3.1. Data

The study will be undertaken via primary data from the first wave of MARS survey that has been conducted in 2018 by the Social Wellbeing Research Centre (SWRC) at the Faculty of Economics and Administration, University of Malaya[1]. As Malaysians come from various economic backgrounds, this study intends to use the first wave of the Malaysian Ageing and Retirement Survey (MARS) that has been conducted in 2018, to capture the information that is needed for this study. Accordingly, the survey has been collected from Malaysians across a broad spectrum of socio-economic backgrounds.

For this study, aspects of health, health utilisation, psycho-social and cognition are not its focused. The benefit of using MARS data is because future studies can be built upon this study, where an exploration of the behaviour of the respondents is collected across many years. In this regard, it is near 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 5613 interviews[2] were completed across 3,384 households. The age of respondents collected was 40 years old and above. This selected variable is

[1] 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 https://swrc.um.edu.my/research/mars/.

[2] One response was omitted due to lack of reporting consistency which brings the total response rate to 5612 responses.

due to the fact that 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), Thus, to include younger respondents would risk skewing the results of the data analysis. Additionally, the age floor used is in line with previous academic studies and industry measurements where the six stages of retirement and process of retirement planning begin almost two decades prior to retirement age (Noone, Stephens & Alpass, 2010; Lee, 2021). While the MARS survey targeted households, the information collected was on an individual basis. Should there be more than one eligible member in a selected household, a maximum of the three oldest eligible members would be selected as possible respondents (Mansor et al., 2019).

3.2. Theoretical framework

The model focuses on foresight as the imperative for retirement savings, given that it requires long-term planning, whereby self-control is imperative as immediate consumption is always more tempting than delayed consumption, and habits is imperative given that good habits will ensure a healthy level of self-control and successful dealing with problems that are associated with self-control. The model begins with incorporating self-control which contain elements of temptation, internal conflict and willpower through the 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. Lifetime income stream is given by equation (1):

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

For simplicity, this model assumes 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 as represented in Eq. (2):

$$C = C_1 + C_2 + C_3 + \cdots + C_{T-1} + C_T \tag{2}$$

The budget constraint is therefore the total consumption being equal to lifetime wealth i.e., $\sum_{t=1}^{T} C_i = LW$. In this model, the conflict that is associated with self-control is captured by contrasting time horizon of the doer and the planner, where the doer is assumed to be extremely short-sighted (myopic) and is only concerned with current consumption while the planner is focused on maximising lifetime doer utilities. This is called the planner-doer framework where an individual is posited to exhibit two sides: 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 marginal propensity to consume in traditional microeconomics.

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 maximum feasible consumption at period t. Instead, the planner will choose a smaller consumption at period t. This model assumes that the 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 the act of willpower ($W_t(C_t)$), and thereby is notated with $Z_t(C_t)$. Therefore, this relationship is given as in Eq. (3):

$$Z_t(C_t) = U_t(C_t) + W_t(C_t) \tag{3}$$

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 the planner and the doer. Will power is effective only when $Z_t(C_t) \neq U_t(C_t)$ and $W_t(C_t) \neq 0$.

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

This model firstly assumes that the 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 the 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 the willpower effort becomes more painful (disutility) when additional willpower is applied. Consumption will then be reduced in the face of the 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 in which it is the rational counterpart of an individual's personality, the model associates the neo-classical utility function $V(\bullet)$ 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 that willpower is costly, the planner will seek other means to reduce willpower costs and to achieve self-control.

One alternative to willpower is the restriction of 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 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 in the future would then have no need to exercise willpower. In essence, the planner will choose consumption that maximises 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 that fits perfectly to the life cycle consumption path (consumption smoothing).

Therefore, it can be implied that the traditional Life Cycle Hypothesis a special case of the Behavioural Life Cycle, i.e., when willpower effort, $\theta = 0$ and the first best rule that is available to the planner. However, zero willpower effort rarely happens as there is a limited number of pension plans and that 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, as in equation (4).

$$D = \left[\frac{\partial Z_t}{\partial \theta_t} \times \frac{\partial \theta_t}{\partial C_t}\right] - \frac{\partial Z_t}{\partial C_t} > 0 \tag{4}$$

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 the willpower costs low. These include habitual rules that should be simple as complex rules would require conscious thinking while habits are subconsciously complied. Exceptions that are made on 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 the different willpower effort costs, the three mental accounts' balances can be included in the model. The theory focuses first on the current income (first mental account) where it postulates that the higher the temptation, the higher the willpower cost that is required to choose a certain consumption level that is lower than the current income account balance (denoted as M_t). At any $C_t < M_t$, increased temptation will make the doer worse off as presented in equation (5):

$$\frac{\partial Z_t}{\partial M_t} = \frac{\partial W_t}{\partial M_t} + \left(\frac{\partial W_t}{\partial \theta_t} \times \frac{\partial \theta_t^*}{\partial M_t}\right) > 0 \tag{5}$$

where, $\frac{\partial\left[\frac{\partial Z_t}{\partial \theta_t} \times \frac{\partial \theta_t}{\partial C_t}\right]}{\partial M_t} < 0$ 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 a higher willpower to spend just RM200 rather than a person whose monthly salary is RM1,200 (which means, the more a person have, 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, successive increments produce less negative impact. For example, given a spending of RM200, the impact on temptation on the additional amount of salary of RM1,000 (from RM4,000 to RM5,000) involves less willpower effort than the RM1,000 increase from RM1,200 to RM2,200. This means, the same amount to spend presents different temptation levels for the different increases in wealth and income levels.

3.2.1. Mental accounting assumption

The mental accounting involves splitting wealth into three categories, i.e., current income, current asset a future income. They are presented in Table 2 where s is the savings rate:

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

As consumption increases, utility increases at a diminishing rate. This in turn also means that willpower decreases. Once 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. As using 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 for when balance in A is depleted and the individual invades the final account, future income account, F.

The key postulate of the theory is non-fungibility of wealth and the marginal propensity to consume is dependent on the type of account.

3.3. Empirical analysis

In predicting savings adequacy, a framework based on the behavioural lifecycle theory- as is shown below, is adopted for this study. The Behavioural Life Cycle hypothesis (Shefrin & Thaler, 1988) posits that people mentally frame wealth as belonging to either current income, current asset, or future income, and this has implications for their savings adequacy as the accounts are largely non-fungible and the marginal propensity to consume out of each account is different. Equation (6) represents the framework where savings adequacy is a factor of wealth (represented by non-fungible categories), consumption (represented by non-fungible categories, which will be discussed in later sections) and demographic factors:

$$P(Savings\ \ Adequacy) : F(wealth, consumption, demographic\ \ factors) \tag{6}$$

The behavioural element from the behavioural lifecycle theory is captured with the assumption of mental accounting where the type of wealth and consumption is divided into several categories. This is done as a measure to manage finances and to attain optimal utility when considering asymmetric information that is faced by an individual.

3.3.1. Dependent variable

The dependent variable, i.e., savings adequacy which is binary (coded yes or no to having saving adequacy) is approximated by comparing the total wealth of a person in retirement with the amount that is needed to sustain consumption in retirement years.

For this study, EPF's recommended amount as per "Belanjawanku" booklet was found to be more suitable for the research objective to gauge savings adequacy for retirement, as the amount needed in retirement life could be approximated with the amount needed by an elderly couple. This benchmark is suitable as it comes at a time where there is an increasing percentage of Malaysian population who resides in urban areas ("Malaysia- urbanisation 2009–2019 | Statista", 2020).

In this regard, the minimum total amount to sustain consumption in retirement is RM37,080 per year multiplied with the years remaining from retirement at age 60 (or current age for current retirees) to age 99 with an assumed discount rate of 3%. The assumed discount rate is from the average discount rate in Malaysia[3]. 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 expectation of longevity whereas a person lives longer, they may need to save more to sustain their consumption. Mathematically it is represented as in equation (7):

$$Total\ \ wealth\ \ at\ \ retirement = \begin{cases} (Total\ \ Current\ \ Asset + Total\ \ Future\ \ Income) \times (1+3\%)^{60-age} & if\ \ age < 60 \\ Total\ \ Annual\ \ Current\ \ Income + Total\ \ Asset + Total\ \ Future\ \ Income & if\ \ age \geq 60 \end{cases} \tag{7}$$

Table 2
Categories of wealth.

Current income, I (Most tempted to use for current consumption)	$I = (1-s)Y_t$
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

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 present value of annuity, as represented in equation (8):

[3] https://www.bnm.gov.my/national-summary-data-page-for-malaysia.

$$Total\ \ consumption\ \ in\ \ retirement = \begin{cases} RM37,080 \times \left(\dfrac{1-\dfrac{1}{(1+3\%)^{99-60}}}{3\%}\right) \times \left(\dfrac{1}{(1+3\%)^{60-age}}\right) & if\ \ age < 60 \\ RM37,080 \times \left(\dfrac{1-\dfrac{1}{(1+3\%)^{99-age}}}{3\%}\right) & if\ \ age \geq 60 \end{cases} \tag{8}$$

Should the total wealth exceed or be equalled to the needed amount to sustain retirement consumption, the person is considered as having adequate savings amount.

3.3.2. Independent variables

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

Current assets refer to the sum of land, other properties, shares of the business, insurance, bank savings (fixed deposit, savings, or current account, etcetera), and others, that are combined in Ringgit Malaysia. While future income refers to the sum of home equity, Employees Provident Fund (EPF) savings, properties, Tabung Haji (Islamic Pilgrimage Fund), Unit trust or ASNB or endowment, shares, private retirement schemes and others that are 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 a utility to spend for the next segment once the current segment is exhausted.

Necessities refer to the sum of costs for transportation (petrol, touch 'n' go, public transport, parking, school van, etcetera), electricity, water, Indah Water fee (fee for national wastewater and sanitation company), and food, that is combined in Ringgit Malaysia. Discretionary items refer to the cost of telephone or mobile phone or prepaid, toiletries, house repairs, and others, that are combined in Ringgit Malaysia. Luxury items refer to the costs for internet, Astro or Netflix or TV Box, payment for domestic services, newspapers or 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 expenditure 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 (Malays, 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 have been coded as per the indicated categories, given that the chosen software can capture labels for categorical variables as they are. The analysis considers respondents of the age 40 and above as according to the Life Cycle hypothesis, this is the age where income peaks, and thus would be the most suitable to analyse their savings adequacy. 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 other financial obligations such as mortgages and car loans would come first (Malaysian Financial Planning Council, 2018). Gender is also included in the analysis to investigate whether gender plays a role in determining and predicting savings adequacy. These demographic factors were deemed important for this study as the same demographic factors were chosen in previous studies related to this study.

3.3.3. Empirical model

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 validation of the algorithms in forming reliable models. 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 7 subsets. Once the model is trained, it will be used to make predictions on each of the 7 subsets independently and the performance of these 7 subsets will be averaged. All algorithms were utilized based on machine learning analysis where only the best performing model based on a set of assessment metric is discussed.

As such the empirical model is given as in equation (9):

$$\begin{aligned} p(savings\ adequacy) = {} & \beta_0 + \beta_1(current\ income) + \beta_2(current\ asset) \\ & + \beta_3(future\ income) + \beta_4(necessities) \\ & + \beta_5(discretionary\ items) + \beta_6(luxury\ items) \\ & + \beta_7(age) + \beta_8(gender) + \beta_9(ethnic) \\ & + \beta_{10}(marital\ status) + \beta_{11}(education) \\ & + \beta_{12}(employment\ status) + \beta_{13}(household\ size) \end{aligned} \tag{9}$$

It must be noted that the expression for the above model is not the actual functional form; rather it is a novel interpretation of 'p (savings adequacy)'. 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 predicting savings adequacy. The algorithms of these supervised machine learning include Naïve Bayesian, Generalised Linear Model (GLM), Logistic Regression, Artificial Neural Network (ANN), Decision Tree, Random Forest, and Gradient Boosted Trees. These methods will be adopted and assessed to see which can best predict savings adequacy. Such methods of comparing performance of different machine learning models have been adopted in previous studies such as the study by Petropoulos et al. (2020).

In this study, the RapidMiner Studio (RapidMiner) version 9.9 Education Edition software is used for the purpose of data analysis. Developed in 2001 by Ralf Klinkenberg, Ingo Mierswa, and Simon Fischer, this software was suitable for analysis. The simple yet powerful algorithms can detect multidimensional and non-linear relationships that savings adequacy 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).

3.3.4. Predictive models

Predictive Modelling refers to a set of statistical models that first identifies a relationship between dependent and independent variable. A model then takes a set of independent variables to predict an outcome, i.e., the dependent variable. In this study, a statistical analysis in the form of model building through machine learning is chosen over econometrics to exploit machine learning's capability of detecting patterns or relationship within the data to lower the risk of exclusion of important variables in the process of designing a system to predict adequate savings.

For this study, the supervised machine learning in the form of predictive modelling is used for examining savings adequacy. The flow of the modelling will be as follows:

The model for Naïve Bayesian in this study is defined as in equation (10):

$$p\left(\frac{x}{y}=k\right)=\prod_{i=1}^{D}p(x_i|y=k) \quad (10)$$

The generalised linear model (GLM) is shown as in equation (11):

$$Y_i=\beta_0+\beta_1X_1+\varepsilon_i \quad (11)$$

The logistic regression is shown as in equation (12):

$$\log\left[\frac{Y}{1-Y}\right]=\beta_0+\beta_1X_1+\beta_2X_2+\beta_3X_3+\cdots+\beta_nX_n \quad (12)$$

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 adequacy (in this case, probability of having adequate savings). In addition, the simplistic modelling assumptions may lead to underfitting for rich and complex datasets.

For these models, the predicted variable is the probability of having adequate savings while the predictor variables range from consumption types and income, among others.

Artificial Neural Network (ANN) would be able to provide a succinct prediction of adequate savings and therefore, is considered for this study's analysis. The model is given- as in equation (13):

$$\log\left(\frac{\widehat{p}}{1-\widehat{p}}\right)=\widehat{m}_{00}+\widehat{m}_{01}\bullet L_1+\widehat{m}_{02}\bullet L_2+\widehat{m}_3\bullet L_3 \quad (13)$$

Despite its low level of interpretability, the ANN is useful to predict binary outcome with $\log\left(\frac{\widehat{p}}{1-\widehat{p}}\right)$ as the outcome variable (prediction of adequate savings). The main neural network regression equation receives the same logit link function that is featured in logistic regression. As with logistic regression, the weight estimation process changes from least squares to maximum likelihood.

ANN has hidden internal working which may not be readily understood and is prone to overfitting, where it also models the data's errors. 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.

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, random forest enables many weak or weakly-correlated classifiers to form a strong classifier.

Gradient boosted trees model is also considered for this study, where the model is given- as in equation (14):

$$F_M(x)=F_0+v\beta_1T_1(x)+v\beta_2T_2(x)+\cdots+v\beta_MT_M(x) \quad (14)$$

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 ($T_1\cdots T_M$). $F_M(x)$ is the prediction of savings adequacy.

However, for the purpose of this study, a seven step assessment metrics is introduced to determine the best algorithm to predict savings adequacy. 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 the ROC curves of all algorithms, where the algorithm with the biggest area under the curve is judged as the best performing model for this evaluation metric. The seven-assessment metrics are in Table 3:

Table 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 have been 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 operation 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, the true positive rate (otherwise known as recall or sensitivity) is presented as below: $True\ positive\ rate=\frac{True\ Positive}{True\ Positive+False\ Negative}$ While the 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 that are made by the model.
4	Precision	Precision is defined as the proportion of positive classification that is made by the model that has been corrected over all that is 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.
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 it 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.

Table 4
Demographic breakdown.

Demographic Factors	Frequency (n = 5612)	Percent (%)
Gender		
Female	3132	56%
Male	2480	44%
Ethnic		
Bumiputera	4,377	78%
Chinese	622	11%
Indian	452	8%
Others	161	3%
Marital Status		
Married	4353	78%
Single	1259	22%
Education		
No schooling	674	12%
Primary school	1612	29%
Secondary School	3058	54%
Tertiary	268	5%
Employment Status		
Retired	1069	19%
Unemployed	2367	42%
Working now	2176	39%
Number of Dependents		
1–5	4434	79%
6–10	1093	19%
11 and above	85	2%

Table 5
Weight Readjustment for Gender and Ethnic Variable.

Gender	Population ("000)	%	Sample	%	Weighting adjustment
Male	5,019	50%	2480	44%	1.14
Female	4963.7	50%	3132	56%	0.89
Ethnic					
Bumiputera	5723	57%	4377	78%	0.74
Chinese	2859.8	29%	622	11%	2.58
Indians	732.9	7%	452	8%	0.91
Others	667	7%	161	3%	2.33

4. Results and discussion

4.1. Descriptive analysis on demography

4.1.1. The demographic breakdown is represented in

Table 4.To reduce bias in data, a post-stratification weight readjustment was conducted on the variable gender and ethnicity 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. The weight readjustment is as shown in Table 5:

4.2. Prediction and fit

The summary of performance for each algorithm is presented in.

4.2.1. Accuracy

Table 6.In this performance metric, the decision tree model has performed the best at 96.1% accuracy, while the Naïve Bayesian model has the least performance at 5.5%.

4.2.2. Classification error

The decision tree has performed the best at 3.9% while the Naïve Bayesian model has the least performance at 94.5%.

4.2.3. Area under Receiver Operating curve (ROC) (AUC)

The AUC curves that are plotted using the RapidMiner system are as shown below:

In this view, the Logistic Regression model has the best AUC curve (light blue curve), while the Naïve Bayes (dark blue curve) has the least performance.

4.2.4. Precision

The models that have performed best are the ANN and the decision tree models at 100% each, while the model that has the least performance is the Naïve Bayesian model at 5.0%.

4.2.5. Recall (also known as sensitivity)

Most of the models performed where the best recall rate was the generalised linear model, logistic regression model, random forest model, and gradient boosted trees model, respectively at 100% each. The model that has least performed is ANN at 7.9%.

4.2.6. F measure

The model that has the highest F measure is the decision tree model at 46.7%. The model that has the least performance is the Naïve Bayesian model at 9.4%.

4.2.7. Specificity

The ANN and decision tree models scored best at 100% specificity. The Naïve Bayesian model scored at 0.6%. The rest of the models had scored 0.0%.

4.3. Best prediction model

In this study, it is found that the decision trees model is the best model to predict savings adequacy, as it has performed the best for accuracy, classification error, precision, F measure, and specificity, as compared to the other models. As for AUC, the decision tree model scored highly at 73.7%. As for specificity, it has scored at 31.1%.

The decision tree model has maximal depth of 15 branches. A visual depiction of the decision tree is provided in Fig. 5. Readers are invited to refer to a discussion by Kuznetsova (2014) for a further understanding of the decision tree model.

The model becomes meaningful by analysing the attributes' weight, where attributes with higher weight are considered more relevant and influential to the dependent variable. In this regard, decision trees are proven to be suitable for this study as it can cater to this study's mid-size data together with its mix of continuous and discrete attributes. As can

Table 6
Breakdown of evaluation metrics measurements for algorithms.

	NB	GLM	LR	ANN	DT	RF	GBT
Accuracy	5.5%	5.7%	5.7%	94.7%	96.1%	5.7%	5.7%
Classification Error	94.5%	94.3%	94.3%	5.3%	3.9%	94.3%	94.3%
AUC	34.8%	81.2%	91.4%	72.8%	73.7%	77.6%	88.0%
Precision	5.0%	5.7%	5.7%	100.0%	100.0%	5.7%	5.7%
Recall	87.2%	100.0%	100.0%	7.9%	31.1%	100.0%	100.0%
F measure	9.4%	10.7%	10.7%	14.5%	46.7%	10.7%	10.7%
Specificity	0.6%	0.0%	0.0%	100.0%	100.0%	0.0%	0.0%

Note. NB = Naïve Bayes; GLM = Generalised Linear Model; LR = Logistic Regression, ANN = Artificial Neural Network; DT = Decision Tree; RF = Random Forest; and GBT = Gradient Boosted Trees.

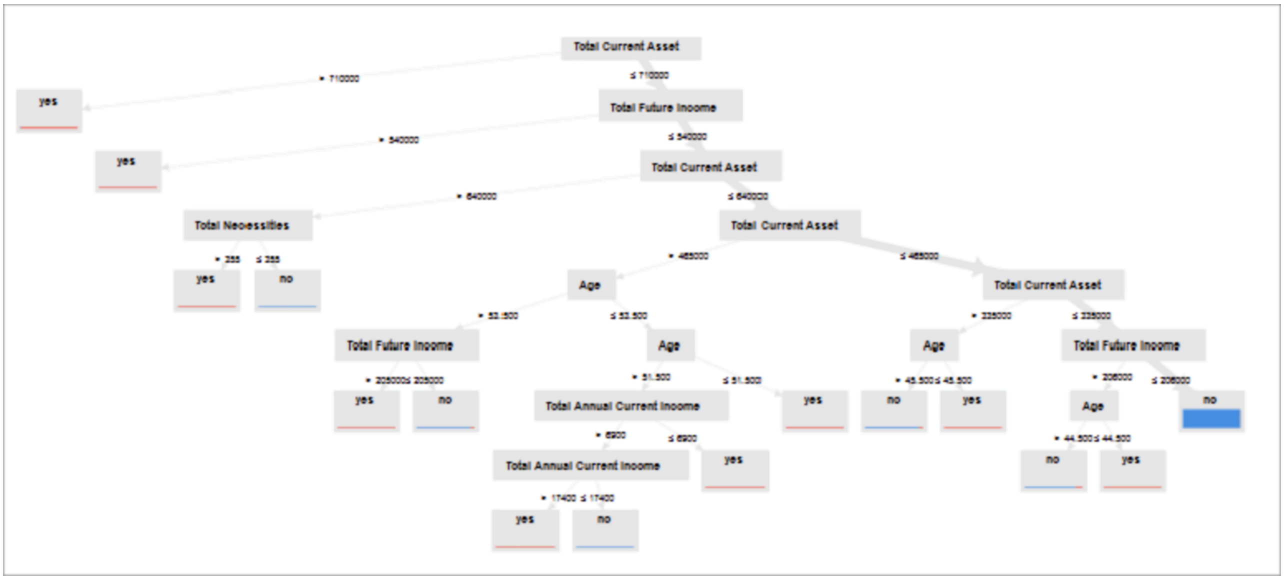

Fig. 5. Visual Depiction of Decision Tree model.

Table 7
Weights of attributes for decision tree model.

Attribute	Weights
Total Luxury Items	0.083
Total Current Asset	0.039
Education	0.028
Employment Status	0.024
Ethnic (Bumiputera)	0.022
Total Future Income	0.018
Total Discretionary Items	0.005
Ethnic (Chinese)	0.005
Total Annual Current Income	0.003
Household Size	0.002
Age	0.002
Total Necessities	0.001

be seen from the top branch decision tree figure, those with current assets amounting to more than RM71,000, are most likely to have adequate savings. Should it be less, the next branch indicates that the amount of future income must be more than RM54,000 to still be considered as having higher likelihood of adequate amount of savings. The flow of criteria is clear and easy to understand. In essence, the decision tree model is the optimal model as it is interpretable as well as being a good predictive model due to its high accuracy rate. This decision tree is optimal to be a tool for diagnosis for determining a person's chance of achieving adequate savings. Together, the benefits of this decision tree model form the merit of this study's proposed method.

The most influential independent variable is Total Luxury Items (expenditure), followed by Total Current Asset. The weightage of the independent variables on the dependent variable is presented in Table VI. In this regard, it is known that the current asset highly positively influences savings adequacy, while the expenditure on luxury items highly negatively influences savings adequacy. An increase in current asset positively impacts savings adequacy, while an increase in expenditure on luxury items has a negative impact on savings adequacy. This departs from the general perception that necessity items that form the bulk of expenditure for middle income and lower-income households influence savings adequacy greatly.

The most influential independent variable is expenditure on luxury items followed by total current asset has the most weightage on savings adequacy. The weightage of the independent variables on the dependent variable is as in Table 7:

To enhance probability of savings adequacy in an individual, an individual is encouraged to not only actively find ways to increase the current asset by putting maximum effort towards investing prudently or via diversifying current income streams to enhance asset accumulation capability. Rather, the individual must also identify and minimise his or her expenditure on luxury items such as Astro or Netflix or TV Box, payment for domestic services, newspapers or magazines, and membership fees.

It is also worth noting that any exclusion of variables will impact all the models that are generated from the seven algorithms' performance negatively, hence, it is important to maintain the independent variables in the models as they are.

5. Conclusion

The decision tree model was found to be the best prediction model to predict savings adequacy as it performed well across all evaluation metrics. Due to consideration of the mental accounting theory, the model has found that the mental accounting categories do have predictive power on savings adequacy. It is found that the current asset rather than the future income has a bigger positive predictive influence on savings adequacy. It is also apparent in the finding that luxury spending rather than necessity spending negatively influences the prediction of savings adequacy.

5.1. Contributions to practice

This implies new policy directions by regulatory bodies and the government of Malaysia, and other similar emerging economies where evaluation of savings adequacy should rely not only on the current income but also the current asset of individuals. Likewise, more education on investing can be introduced to the public. To enhance opportunities, upskill or skills diversification programmes should be more available and provided by the government and related organisations. With this, it is learnt that promoting active or productive ageing is important despite having a proper or mandatory channel to secure savings from earned income.

In addition, financial education programmes can also be introduced to raise the awareness on money management and the importance of being financially aware of personal expenditure, which in general is to minimise spending on luxury items while enhancing current assets. Consultants and financial planners should also be cognisant of the findings where mental accounting matters and to be at the forefront to raise awareness of their clients in order to ensure that they are more prepared for retirement.

Governments, policymakers, and financial organisations are also invited to adapt this model using the decision tree algorithm as part of a publicly available budgeting tool to enhance the financial literacy level of individuals on top of using the model as a tool to re-evaluate the existing structure of future income landscape in Malaysia.

6. Research limitation and way forward

One of the key limitations of this study is the use of a cross-sectional data, where the usage of this data makes it possible to establish a relationship without establishing the direction of causality. Moving forward, researchers are encouraged to deploy the machine learning model with successive waves of MARS data to enhance the quality and efficacy of the decision tree model while establishing the direction of causality between the variables. Given its relatively user-friendly and deployable nature, the model developed in this study can learn with each successive waves of MARS data in the future; the model can also be used with comparable data across other jurisdictions.

Another limitation of this study is that the age of the respondents is constrained to 40 years and above. While in line with previous studies (Noone, Stephens & Alpass, 2010; Asian Institute of Finance [AIF], 2015; Lee, 2021), other researchers are invited to study the savings adequacy from a cohort perspective stretching to those younger than 40 years old, given that each cohort displays different spending and savings trends moving forward. Specifically, another limitation of this study is that assets are reported from an individual basis in the MARS survey. This departs from the general perception that assets are jointly owned for married couples.

Distinctly, the measure of adequacy is based on the amount that is needed for an elderly couple in Klang Valley, as per "Belanjawanku" 2019 booklet that has been published by EPF. While a large population in Malaysia lives in urban areas ("Malaysia- urbanisation 2009–2019 | Statista", 2020) much comparable to living standards in Klang Valley, it is encouraged for researchers to replicate this study using adequacy measure that considers the different urban and rural living standards context to obtain a wholesome picture of savings adequacy for Malaysians.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eswa.2022.117502.

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