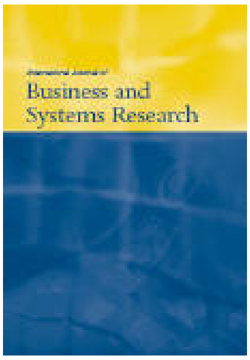

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Determinants of asset allocation decisions of robo-advisors in the Asia-Pacific region

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Abstract: This paper investigates the determinants of asset allocation decisions of robo-advisors in the Asia-Pacific region based on a sample of 30 robo-advisors in seven Asia-Pacific economies for the period 2022 to 2024. The results reveal that investors' risk profiles have a significant positive influence on the percentage of equity in the recommended portfolio. It is further observed that aggressive investors are allocated with more equities than investors with conservative and moderate risk profiles. In terms of fund characteristics, the number of portfolios offered has a significant positive impact on the percentage of equity in the recommended portfolio, especially for aggressive investors. Contrarily, expertise in fixed income class exerts a significant negative effect on the percentage of equity in the recommended portfolio, particularly for conservative investors. Lastly, macroeconomic factors, in particular inflation rate, negatively influence the percentage of equity in the recommended portfolio of conservative investors.

Keywords: Asia-Pacific; asset allocation; financial technology; modern portfolio theory; MPT; portfolio investments; robo-advisors.

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1 Introduction

Financial technology (FinTech) has been a prominent technology disruption within the financial industry recently, in which it integrates innovation and technology into financial services (Aw et al., 2024). This emerging technology leverages heavily on the Internet of Things and advanced information technologies such as blockchain, cloud computing, big data and artificial intelligence to improve and surpass traditional financial approaches. One of the fast-growing FinTech applications is robo-advisor, which essentially is a digital financial advisor that uses rational logic, statistical rules and deep machine learning algorithms to analyse financial products' characteristics and investors' profiles to provide optimal personalised portfolio recommendations. After establishing the initial portfolio recommendations, robo-advisors automatically and continuously monitor and rebalance the asset weightage in the portfolio according to changes in the financial products, investors' profiles or market conditions in a real-time basis (Helms et al., 2022).

Extant literature has documented the benefits of robo-advisors. For instance, Liu et al. (2021) assert that robo-advisor users outperform other investors by having fewer daily losses because robo-advisors are more flexible in conducting portfolio adjustments such as shifting funds to less risky securities during market downturns. Moreover, robo-advisors are able to process a large quantity of information, thus facilitating complicated investment decisions, as well as are unbiased when assessing investors' risk profiles and advising on asset allocations (Bhatia et al., 2022). Besides, it is easy and convenient to obtain advice from these digital platforms which are accessible round-the-clock using computers or smartphones (Nain and Rajan, 2023).

Notwithstanding these benefits, prior research has highlighted that one of the major issues related to robo-advisors is these digital platforms are often regarded as a 'black box' because the algorithm systems used for analysing, matching and recommending the portfolios are unpublished or unknown (Torno et al., 2021). These processes are inevitably opaque due to the complicated structures of deep learning using artificial intelligence algorithms, where even the system developers may not be able to fully explain the processes (Kato, 2020). Another related issue is past studies have demonstrated that robo-advisors utilise limited information from the online risk assessment questionnaires to formulate portfolio recommendations (Puhle, 2019; Tertilt and Scholz, 2018). As a result, investors could not ascertain how robo-advisors derive their portfolio recommendations and what information they depend on. This makes it challenging for the investors to identify the causes of any potential losses or gains in their portfolios (Xiao and Adekola, 2021).

In order to unravel this black box, Kato (2020) has urged researchers to develop a model to explain the relationship between robo-advisors' inputs and outputs, or in other words, to explore the determinants of asset allocation decisions by the robo-advisors. Echoing Kato (2020), this paper asserts that very little is known about how the asset allocation decisions are generated by these digital platforms, especially in the Asia-Pacific context. Robo-advisor is a relatively new FinTech concept in this region as compared to Western developed countries, particularly the USA where the first robo-advisor, Betterment was launched in 2010, while robo-advisor was introduced in the Asia-Pacific less than a decade ago.

Moreover, extant research on the determinants of asset allocation decisions has largely concentrated on human advisors or investors but there is a dearth of studies which have explored robo-advisors. For example, past literature has revealed that investors' risk attitude and personal characteristics influence the asset allocation decisions of human advisors or investors (Cavezzali and Rigoni, 2012; Zhang et al., 2018). There are, however, rather limited studies which examine the relationship between investors' risk profiles and asset allocation decisions by robo-advisors (Boreiko and Massarotti, 2020; Scherer and Lehner, 2021). Besides, these papers only focus on Western countries, especially the USA. Thus, it is unclear whether this relationship holds true in other regions such as the Asia-Pacific.

Additionally, this paper contends that fund characteristics may also influence the asset allocation decisions of robo-advisors. So far, fund characteristics have largely been investigated from the fund performance perspective (Choi et al., 2016; Joenväärä et al., 2021). Nonetheless, the literature on how fund characteristics relate to the asset allocation decisions by either human or robo-advisors is rather scarce (Boreiko and Massarotti, 2020; Tertilt and Scholz, 2018). Furthermore, extant literature has documented the impact of macroeconomic factors on the performance of different asset classes and investors' asset allocation decisions (Ilmanen et al., 2014; Shao et al., 2023; Sheikh and Sun, 2012). According to Helms et al. (2022), although the majority of robo-advisors claim that they will rebalance the portfolio weights according to market conditions, these platforms do not publish the adjustment algorithms. It is imperative for robo-advisors to react to changing market conditions to estimate the level of risks and price the products correctly (Guo, 2020). To date, very few studies have considered the influence of macroeconomic factors on robo-advisors' asset allocation decisions (Ahn et al., 2020).

Against this background, this paper aims to address these research gaps by investigating the determinants of asset allocation decisions of robo-advisors in the Asia-Pacific region, where we draw on a sample of 30 robo-advisors in seven economies in this region, i.e., Malaysia, Singapore, India, Hong Kong Special Administrative Region (SAR), Taiwan Province of China (Taiwan), South Korea and Japan over the period 2022 to 2024. Specifically, we aim to identify how investors' risk profiles, fund characteristics and macroeconomic factors are related to robo-advisors' asset allocations.

The contribution of the research is multi-fold. First, we contribute to the literature on the construction of efficient portfolios by applying Markowitz's (1952) modern portfolio theory (MPT). The MPT has been broadly applied to evaluate and generate optimal portfolios that match investors' risk attitudes with expected returns while gaining diversification benefits (Chang et al., 2020; Junaid et al., 2020; Verdiyanto, 2020). According to the MPT, investors or advisors have to allocate their resources into different asset classes, sectors or countries to achieve diversified optimal portfolios. Nevertheless, the majority of past studies only focus on human practices (Kaplan and Siegel, 2011; Ünlü and Xanthopoulos, 2021), whereas this research is conducted based on robo-advisors. Hence, this study enriches our understanding of the applicability of the MPT for asset allocation decisions using automation or machine learning ability of algorithm systems.

Second, this paper broadens the literature on the determinants of asset allocation decisions by robo-advisors. Extant research on robo-advisors has predominantly focused on the adoption of robo-advisors (Aw et al., 2024; Roh et al., 2023; Sabir et al., 2023) and the comparison with human advisors (Liu et al., 2021; Zhang et al., 2021). However, there is a paucity of studies on how the algorithm systems work and what affects robo-advisors' asset allocation recommendations. Therefore, we contribute new insights on the influence of investors' risk profiles, fund characteristics and macroeconomic drivers on robo-advisors' asset allocation decisions by conducting a multi-country study covering seven Asia-Pacific economies.

The rest of the paper is structured as follows. Section 2 reviews the literature and develops testable hypotheses. Section 3 outlines the data and methodology. The results are analysed and discussed in Section 4, while Section 5 performs additional robustness tests. Section 6 provides the concluding remarks.

2 Literature review and hypotheses development

2.1 Modern portfolio theory

Markowitz (1952) proposes the expected return-variance rule or classical MPT for portfolio selection and management which assumes that investors should expect a certain degree of risk and uncertainty while desiring maximum returns. To minimise the variance of returns, investors should diversify their funds among different securities with returns that are not significantly correlated. Investors will select their optimal portfolios from a set of efficient mean-variance combinations based on their risk-return preferences.

Numerous studies have applied the MPT in their portfolio construction and evaluation. For instance, Kaplan and Siegel (2011) illustrate using a computer software how the MPT can be adopted in asset allocation and claim that this application is more useful to reduce portfolio risk arising from the correlation between returns of various securities. Ünlü and Xanthopoulos (2021) develop an algorithm model based on the MPT, where the problem associated with providing different solutions with varying performance for every run is minimised. Gerhana et al. (2021) demonstrate how the MPT is applied in the experimental robo-advisor algorithm, where the system allocates assets according to investors' risk profile and historical performances provided in the system interface. Taken together, the MPT is presently the most ubiquitous theory or rule to be coded in robo-advisors for optimal portfolio recommendations, where according to Muganda and Kasamani (2023), approximately 80% of robo-advisors adopt the MPT in their asset allocation decisions.

2.2 Investors' risk profiles and asset allocation decisions of robo-advisors

The relationship between investors' risk profiles and human asset allocation decisions has been investigated in numerous literatures but more recently, some researchers have extended their studies to cover robo-advisors' asset allocation choices. For example, before the robo-advisor era, Corter and Chen (2006) have developed an interactive and adaptive computer-implemented instrument called the risk tolerance questionnaire to evaluate investors' risk attitudes and propensities. The authors investigate the consistency of the questionnaire scoring with the investment portfolio risks and report that risk attitudes in investment do predict the actual investing behaviour.

In a similar scope, Cavezzali and Rigoni (2012) report that investors' profiles, especially their perceived risk attitude, influence the asset allocation recommendations by human advisors in Italy. Hyll and Irrek (2015) examine the relationship between risk aversion and asset holdings in Germany and find that risk attitudes are significantly related to individual portfolio choices. Similar evidence is provided by Alserda et al.

(2019) who analyse the adequacy of pension funds in reflecting their members' risk preferences in the Netherlands. Due to the difficulty in obtaining each member's individual risk preference, most pension plans force their members to adopt the same asset allocation. The authors report significant welfare losses of being forced into the same asset allocation relative to the customised portfolios generated via simulation because the former does not match with the individual risk attitudes.

Turning to robo-advisors, Boreiko and Massarotti (2020) investigate the factors influencing asset allocation recommendations of robo-advisors in the USA and Germany. They find investors' risk profiles as a significant determinant, where conservative investors are given lower equity allocation. Scherer and Lehner (2021) examine the relationship between investor characteristics and asset allocation decisions of robo-advisors in the USA and report that more equities are allocated for investors with lower risk aversion. Tertilt and Scholz (2018) analyse the association between investors' risk preferences and portfolio recommendations of robo-advisors in the UK, USA and Germany and find that higher equity allocations are offered to aggressive investors. Helms et al. (2022) segregate the investors into different risk classes which represent their risk propensity and examine their influence on the robo-advisors' portfolio recommendations in Germany, the UK and USA. However, the authors report that there is a wide difference in the portfolio recommendations offered by robo-advisors in each risk class in the context of risk-return trade-offs. Hence, they conclude that robo-advisors do not adopt uniform or standardised investment strategies for all risk classes and their strategies or recommendations depend on individual robo-advisors.

Based on the preceding discussions, extant studies have demonstrated the influence of investors' risk profiles on asset allocation decisions. However, these studies, especially in the context of robo-advisors, have reported inconclusive findings regarding whether the asset allocations performed appropriately reflects investors' risk profiles, and they are predominantly conducted in Western countries. It is unclear a priori whether this relationship holds true in the Asia-Pacific context. This study hypothesises that investors' risk profiles affect the asset allocation decisions of robo-advisors because investors have distinct risk attitudes arising from their personal characteristics or preferences, which may influence their investment choices. In particular, this research expects that conservative investors are given lower equity allocations while aggressive investors are given higher equity allocations by these robo-advisor platforms.

H1 There is a relationship between investors' risk profiles and asset allocation decisions of robo-advisors.

2.3 Fund characteristics and asset allocation decisions of robo-advisors

2.3.1 Number of portfolios offered

Robo-advisors generally offer a number of standardised, rather than customised, portfolios for cost efficiency. In their research on the portfolio recommendations of robo-advisors in the UK, USA and Germany, Tertilt and Scholz (2018) assert that the higher the number of portfolios offered, the more precisely the system could match the customer risk profile to an ideal portfolio. Nonetheless, the authors find that the quality of portfolio recommendations is not consistent with the number of portfolios offered.

Correspondingly, they conclude that the deficiencies in risk profiling assessment are not able to be compensated by a high number of standardised portfolios.

Moreover, robo-advisors classify investors into certain risk categories based on the answers provided in the questionnaires and these risk categories are often related to the number of standardised portfolios. This motivates Boreiko and Massarotti (2020) to analyse the determinants of portfolio recommendations by robo-advisors in Germany and the USA. However, the authors report that the number of portfolios offered is not a significant determinant.

Due to the paucity of research being conducted on this area, this paper intends to extend the investigation on how the number of portfolios offered influences robo-advisors' asset allocation decisions in the Asia-Pacific region. This research hypothesises that the number of portfolios offered affect the asset allocation decisions of robo-advisors because they typically classify investors into certain risk categories which are often related to the number of standardised portfolios offered by these digital platforms.

H2a There is a relationship between the number of portfolios offered and asset allocation decisions of robo-advisors.

2.3.2 Expertise in different asset classes

Extant literature has documented that fund management firms may adopt diverse investment strategies. For instance, Choi et al. (2016) examine the existence of economies of scale within the fund management industry in the USA. They find that fund performance is adversely associated with individual fund size but is positively related to total fund size, suggesting that economies of scale are exhibited at the entire firm level. The authors conclude that investment firms allocate resources, including income streams, in favour of funds with higher economic values to enjoy scale benefits. This notion is supported by Camanho et al. (2022) who find that smaller fund size and funds with greater concentration in fewer stocks tend to engage in more portfolio rebalancing when encountering return differentials.

Research on the association between robo-advisors' expertise in different asset classes and their asset allocation decisions are conspicuously absent except for a recent paper by Boreiko and Massarotti (2020) on the determinants of portfolio recommendations by robo-advisors in Germany and the USA. The authors argue that besides achieving economies of scale via substantial cost savings on inputs such as human capital, robo-advisors may also exploit economies of scale by concentrating on a limited number of financial products or asset classes in which they have expertise in. They report that robo-advisors' expertise in certain asset classes plays a significant role in influencing their asset allocation decisions, where robo-advisors with more expertise in equities tend to allocate more equities in their recommended portfolios. Similar observation is reported for fixed income assets but not for other asset classes.

Based on the aforementioned discussions, it can be observed that there is a relationship between robo-advisors' expertise in different asset classes and their asset allocation decisions. Nevertheless, due to the very limited evidence furnished by extant literature, it remains unclear whether this relationship is generalisable to other economies or countries. This paper hypothesises that the expertise in different asset classes affect robo-advisors' asset allocation decisions because robo-advisors may be motivated to exploit economies of scale to remain price competitive by allocating investors' portfolios in a limited number of financial products or asset classes in which they have expertise in.

H2b There is a relationship between expertise in different asset classes and asset allocation decisions of robo-advisors.

2.4 Macroeconomic factors and asset allocation decisions of robo-advisors

2.4.1 Inflation rate

Past literature has documented that inflation rates may affect asset allocation decisions because different asset classes may respond differently to fluctuations in inflation rates. For example, Brière and Signori (2009) investigate how inflation rates affect different asset classes and the optimal asset allocation. The inflation-hedging properties for each asset class are examined over two economic conditions, i.e., stable and volatile environment. The authors report that conservative investors should mainly hold cash for the short-term during volatile economic conditions and allocate more in inflation-linked bonds, equities, commodities and real estate as the investment horizon increases. During stable economic conditions, cash is still essential to hedge against inflation for the short-term but it has to be replaced by nominal bonds, equities and commodities in the long-term. As for aggressive investors, the portfolios should mainly consist of equities and commodities during a volatile economy but more commodities during a stable economy. Hence, the findings demonstrate that optimal asset allocations vary significantly across different phases of the economic cycle and respond to inflation rate fluctuations.

In another related study, Koniarski and Sebastian (2015) analyse the inflation-hedging properties of different assets in the USA. The empirical findings reveal that cash is a superior inflation hedge over all investment horizons. Yet, stocks, bonds and real estate serve as a better hedge against inflation as the investment horizon increases. In the medium-term, bonds provide better inflation protection than stocks but the opposite holds true in the long-term. Meanwhile, real estate exhibits the best inflation-protection qualities in both medium and long-term horizons. Meanwhile, Shao et al. (2023) examine the influence of inflation risk on the optimal investment strategy for defined-contribution pension plan. The authors find that a higher risk-aversion will lead to less allocation in stocks and more allocation in inflation-indexed bonds. Additionally, greater expected inflation rate will result in less proportion being invested in stocks.

The effect of inflation rates on asset allocation decisions is further demonstrated by how they influence the correlation between returns on different asset classes. For instance, Li (2002) analyses the relationship between inflation rate and the correlation between stock and bond returns for the G7 countries. The author reports that uncertainty about long-term expected inflation rates significantly affect co-movements between returns on stocks and bonds. Similar evidence is provided by Namango (2018) who reveals that inflation rates are positively related to stock-bond return correlation in Kenya. During recessions, inflation rate risk and the stock-bond return correlations tend to be higher, which may limit diversification opportunities. In a similar approach, Phoa (2023) reports that inflation rates affect the correlation between stock and bond. This results in low-frequency regime switching between negative and positive correlation regimes.

Meanwhile, there are very limited studies that have explored the influence of inflation rates on robo-advisors' asset allocation decisions. For example, Gu et al. (2019) propose a new investment strategy with deep-learning market prediction for robo-advisors' portfolio optimisation. The authors incorporate numerous macroeconomic factors into the prediction model, including inflation rates, and report that the accuracy of the market prediction model can reach 84.3%.

Collectively, extant literature has demonstrated that inflation rates influence asset allocation decisions because different asset classes react differently to changes in inflation rates and inflation rates affect the correlation between returns on different asset classes. Nevertheless, there is a paucity of research that has explicitly investigated the relationship between inflation rates and asset allocation decisions by robo-advisors. This study hypothesises that inflation rate influences robo-advisors' asset allocation decisions because different asset classes may respond differently to fluctuations in inflation rates and act as a better hedge against inflation for different investment horizons, where greater expected inflation rate will result in more proportion being allocated towards cash in the short-term, bonds in the medium-term and equities in the long-term.

H3a There is a relationship between inflation rate and asset allocation decisions of robo-advisors.

2.4.2 Exchange rate

Prior research has demonstrated that exchange rates may affect asset allocation decisions because different asset classes may respond differently to changes in exchange rates. For instance, Chow et al. (1997) analyse the influence of exchange rates on the returns on stocks and bonds in the USA and find that bond returns are positively related to exchange rate changes across all investment horizons due to the inverse association between changes in exchange rates and domestic interest rates. Meanwhile, stock returns are positively associated with exchange rate changes in the long-run due to the cash flows effects, where the transaction exposure is negative in the short-run but positive in the long-run, while the economic exposure intensifies as the investment horizon lengthens. According to the authors, transaction exposure refers to the risk of changes in exchange rates in the short-run between the time of entering into a foreign currency transaction and its settlement time, whereas economic exposure is the risk that fluctuations in exchange rates may cause future cash flows and firm value to change.

Motivated by the change in exchange rate policy in Egypt, Ahmed (2020) examines the spillover effects of changes in exchange rates on stock returns under both the soft peg and free float exchange rate regimes. The author reports a significant positive association between exchange rate changes and stock returns in both the short- and long-run under the soft peg regime. Meanwhile, only a long-run positive relationship exists under the free float regime. The author concludes that understanding the association between exchange rate fluctuations and stock returns is critical in allocating foreign assets in the portfolio optimally. By contrast, Wong (2017) performs a multi-country study on the association between real exchange rate returns and real stock price returns and reveals that exchange rate has a significant negative association with stock returns in Korea, Singapore, Malaysia and the UK. Camanho et al. (2022) find that equity funds tend to engage in more portfolio rebalancing when there is higher exchange rate risk. Stated differently, greater return differential between local and foreign fund positions reinforces the rebalancing of portfolios among equity funds.

Meanwhile, there is a dearth of studies on the influence of exchange rates on robo-advisors' asset allocation decisions. For instance, Ahn et al. (2020) propose an asset allocation model for robo-advisors using genetic algorithms and the financial market instability index. For their empirical analysis, the authors have included exchange rates as one of the potential determinants of asset allocation decisions of robo-advisors.

To sum, past studies have revealed mixed results on the effect of exchange rates on the performance of different asset classes. However, there are very limited research that has explicitly examined the association between exchange rates and asset allocation decisions by robo-advisors. This paper hypothesises that exchange rate influences robo-advisors' asset allocation decisions because different asset classes may react differently to changes in exchange rates and greater exchange rate movements or risks will lead to more portfolio rebalancing.

H3b There is a relationship between exchange rate and asset allocation decisions of robo-advisors.

3 Data and methodology

3.1 Sample and data

This research is performed on seven Asia-Pacific economies, i.e., Malaysia, Singapore, India, Hong Kong SAR, Taiwan, South Korea and Japan. These economies are selected as the representative major economies of each Asia-Pacific sub-region for the purpose of findings generalisation on the Asia-Pacific as a whole. For example, Malaysia and Singapore in the Southeast Asia region, India in the South Asia region, Hong Kong SAR and Taiwan in the Northeast Asia region and South Korea and Japan in the North Asia region. Moreover, these economies experience a rather similar pace in the development of robo-advisory services, where most of them initiated robo-advisory circa 2016.

Echoing the challenges encountered by Boreiko and Massarotti (2020) in identifying the relevant market players in the robo-advisory industry in the absence of any database which provide a comprehensive list of operational robo-advisors, this paper relies on market reports (FinTech News Hong Kong, 2022; KPMG, 2021) and comparisons of robo-advisors found in various websites to identify the robo-advisory platforms in these Asia-Pacific economies. From these sources, we construct an initial sample of 76 active platforms. However, we only consider robo-advisors which are fully automated without human intervention but exclude platforms which do not publicly disclose the required data. After accounting for these restrictions, the final sample consists of 30 robo-advisors, where seven are from Japan, six are from Malaysia, Singapore and Taiwan, respectively, two are from Hong Kong SAR and South Korea, respectively, and one is from India.

This is a panel data study covering the period from 2022 to 2024. Specifically, data are collected from robo-advisors' official websites and portfolio recommendations as of June 2022 and August 2024. The chosen study period is intended to capture the learning and adjustment patterns made by the algorithms used by the robo-advisors based on machine or deep learning over time. In order to obtain portfolio recommendations from the sample robo-advisors, we are required to fill up the online questionnaires on these digital platforms. For the purpose of comparing the portfolio recommendations across these platforms, we have constructed three general investors' risk profiles, i.e., conservative, moderate and aggressive (see Appendix).

The standardised investors' profiles are used as inputs to fill up the online questionnaires from 30 robo-advisors in June 2022, resulting in a collection of 90 portfolio recommendations. However, due to data restrictions or unavailability, we could only collect the portfolio recommendations from 19 robo-advisors when we repeat the data collection in August 2024, giving us a total of 57 portfolio recommendations. Collectively, this research gathers 147 portfolio recommendations over the entire study period.

This method of creating standardised or general risk profiles for the investors is commonly adopted in research on robo-advisors' asset allocation decisions (Boreiko and Massarotti, 2020; Helms et al., 2022). This standardisation allows the researchers to compare the portfolio recommendations among different robo-advisors in a more effective and uniform manner. Put differently, it allows us to examine the equity allocation recommended by the robo-advisors by just comparing the investors' risk profiles and serves as a good way to control for other demographic variations.

In terms of macroeconomic variables, the year-on-year percentage change in Consumer Price Index (CPI) and average exchange rate of US dollar (USD) per local currency as of June 2022 and August 2024 for each sample economy are gathered from the International Monetary Fund's International Financial Statistics. We also resort to other sources of data such as related government websites to gather any missing data.

3.2 Variable measurement

The dependent variable is the percentage of equity in the recommended portfolios by robo-advisors (*EQU*), measured as the ratio of recommended equity in the recommended portfolio comprising equity, fixed income and other assets (Boreiko and Massarotti, 2020; Helms et al., 2022).

The percentage of recommended equity is calculated as follows:

$$EQU_{ij} = \frac{REQ_{ij}}{REQ_{ij} + RFI_{ij} + ROA_{ij}} \tag{1}$$

where

- EQU_{ij} = percentage of equity in the recommended portfolio by robo-advisor i for investor's risk profile j
- REQ_{ij} = number of equities recommended by robo-advisor i for investor's risk profile j
- RFI_{ij} = number of fixed income assets recommended by robo-advisor i for investor's risk profile j
- $ROAij$ = number of other assets recommended by robo-advisor i for investor's risk profile j.

Table 1 Overview of general investors' profiles

Investors' profiles	*Conservative*	*Moderate*	*Aggressive*
Age	40 years old	40 years old	40 years old
Gender	Male	Male	Male
Education	Upper secondary school	Upper secondary school	Upper secondary school
Occupation	Sales and service personnel	Sales and service personnel	Sales and service personnel
Monthly income	USD2,292.46	USD2,292.46	USD2,292.46
Marital status	Married	Single	Married
Dependant	Yes	No	No
Individual net worth	USD110,038.08	USD110,038.08	USD110,038.08
Investment philosophy	Stable return and minimum loss	Higher return and acceptable loss	Maximum return
Risk tolerance	Low	Medium	High
Investment goal	General investment	General investment	General investment
Investment horizon	5 to 10 years	5 to 10 years	5 to 10 years
Monthly investment amount	USD229.25	USD229.25	USD229.25

The first independent variable is investors' risk profiles. According to the MPT, investors will choose their optimal portfolios from a set of efficient mean-variance combinations based on their risk-return preferences (Markowitz, 1952). Extant literature has demonstrated that the majority of robo-advisors apply the MPT in their asset allocation decisions (Muganda and Kasamani, 2023), where the system allocates assets according to investors' risk profile and historical performances provided in the system interface (Gerhana et al., 2021; Ünlü and Xanthopoulos, 2021). Following Boreiko and Massarotti (2020), we have constructed three general investor profiles with differing risk attitudes, i.e., conservative (*CONSE*), moderate (*MODER*) and aggressive (*AGGRE*) for the purpose of comparing portfolio recommendations. The assembled investors' risk profiles provide the necessary inputs to fill up the online questionnaires from the robo-advisor platforms. Detailed information regarding the construction of these risk profiles is outlined in Appendix. Table 1 presents an overview of the general investors' profiles.

The second independent variable is fund characteristics. There are three proxies for fund characteristics, i.e., number of portfolios offered, expertise in equity class and expertise in fixed income class. The number of portfolios offered (*PORTF*), which is hand-collected by manually counting the model portfolios offered by each robo-advisor on its respective official websites, is included as a proxy for fund characteristics because earlier studies such as Boreiko and Massarotti (2020) and Tertilt and Scholz (2018) contend that robo-advisors with a higher number of portfolios offered could potentially match the customer risk profile to an ideal portfolio more accurately.

In order to capture the robo-advisors' expertise in different asset classes, two measures are adopted, i.e., expertise in equity (*EQEXP*) and expertise in fixed income (*FIEXP*), as previous studies such as Boreiko and Massarotti (2020) and Choi et al. (2016) have shown that robo-advisors may be motivated to exploit the economies of scale to remain price competitive by allocating the investors' portfolios in a limited number of financial products or asset classes in which they have expertise in. For example, robo-advisors with more expertise in equities tend to allocate more equities in their recommended portfolios, while those with greater expertise in fixed income assets are more inclined to allocate more of these financial assets in their recommended portfolios. Robo-advisors' expertise is measured by the weightage of each asset class in the robo-advisors' investment universe as follows:

$$WGH_{ij} = \frac{AST_{ij}}{TTL_{ij}} \tag{2}$$

where

- WGH_{ij} = weightage of an asset class over total assets i in the investment universe of robo-advisor j
- AST_{ij} = number of assets within an asset class i in the investment universe of robo-advisor j
- TTL_{ij} = total number of assets i in the investment universe of robo-advisor j.

Table 2 Variable definitions

Symbol	*Variable*	*Definition*	*Source*
EQU	Percentage of equity in the recommended portfolio	Percentage of equity in the recommended portfolio by robo-advisor i for investor's risk profile j. Refer to equation (1) for details.	Robo-advisors' recommended portfolios
CONSE	Conservative investor's risk profile	Dummy variable equals one if the investor's risk profile is conservative and otherwise zero.	Appendix
MODER	Moderate investor's risk profile	Dummy variable equals one if the investor's risk profile is moderate and otherwise zero.	Appendix
AGGRE	Aggressive investor's risk profile	Dummy variable equals one if the investor's risk profile is aggressive and otherwise zero.	Appendix
PORTF	Number of portfolios offered	The total number of model portfolios offered on each robo-advisor platform.	Robo-advisors' official websites
EQEXP	Expertise in equity class	The weightage of equity in the investment universe of robo-advisor j. Refer to equation (2) for details.	Robo-advisors' official websites
FIEXP	Expertise in fixed income class	The weightage of fixed income in the investment universe of robo-advisor j. Refer to equation (2) for details.	Robo-advisors' official websites
INFLR	Inflation rate	The year-on-year percentage change in CPI.	International Financial Statistics
EXCHR	Exchange rate	The average exchange rate of USD per local currency.	International Financial Statistics

The third independent variable is macroeconomic factors. There are two proxies for macroeconomic factors, i.e., inflation rate and exchange rate. Inflation rate (*INFLR*), which is calculated as the year-on-year percentage change in CPI, is incorporated as a proxy for macroeconomic factor since extant literature has demonstrated that inflation rates influence asset allocation decisions because different asset classes react differently to changes in inflation rates and these asset classes may serve as a better hedge against inflation for varying investment horizons. Consequently, greater expected inflation rate may result in more proportion being allocated towards cash in the short-term, bonds in the medium-term and equities in the long-term (Brière and Signori, 2009; Koniarski and Sebastian, 2015; Shao et al., 2023). Similarly, exchange rate (*EXCHR*), which is measured as the average exchange rate of USD per local currency, is added because prior research has revealed that different asset classes may respond in a different manner to changes in exchange rates and greater exchange rate movements or risks will lead to more portfolio rebalancing (Camanho et al., 2022; Chow et al., 1997; Wong, 2017). A summary of the variables and their symbol, definition and source of data is presented in Table 2.

3.3 Methodology

The model adopted in this study is an extension of the past research by Boreiko and Massarotti (2020). However, these authors only focused on robo-advisors in Germany and the USA and did not take into consideration the effects of macroeconomic variables on robo-advisors' asset allocation decisions. Hence, we intend to fill these research gaps by conducting a multi-country study based on seven Asia-Pacific economies and incorporating macroeconomic variables into the model.

The regression model of this study is as follows:

$$\begin{aligned} EQU_{ij} &= \alpha_0 + \beta_1 MODER_i + \beta_2 AGGRE_i + \beta_3 PORTF_i \\ &\quad + \beta_4 EQEXP_i + \beta_5 FIEXP_i + \beta_6 INFLR_i \\ &\quad + \beta_7 EXCHR_i + \eta_i + \varepsilon_i \end{aligned} \tag{3}$$

where EQU_{ij} is the percentage of equity in the recommended portfolio by robo-advisor i for investor's risk profile j. $MODER_i$ is the dummy variable equals one if the investor's risk profile is moderate and otherwise zero, while $AGGRE_i$ is the dummy variable equals one if the investor's risk profile is aggressive and otherwise zero. $PORTF_i$ denotes the number of portfolios offered, $EQEXP_i$ is expertise in equity class, $FIEXP_i$ is expertise in fixed income class, $INFLR_i$ represents inflation rate and $EXCHR_i$ is exchange rate. η_i are country dummies and ε_i denotes the error term.

This paper employs a least-squares regression incorporating country dummies or the least squares dummy variable (LSDV) approach to control for any unobserved heterogeneity between countries. This is important because unobserved heterogeneity may lead to potential endogeneity issues when they are correlated with the independent variables (Giesselmann and Schmidt-Catran, 2019). Hence, the LSDV estimator yields more consistent and unbiased results than the ordinary least squares method which may be biased and inconsistent when individual-specific effects are present.

4 Results

4.1 Descriptive statistics

Table 3 outlines the descriptive statistics for the variables, whereas Table 4 tabulates the descriptive statistics for the portfolio recommendations by investors' risk profiles. Table 3 illustrates that the average percentage of equity in the recommended portfolio is 0.4511 while the standard deviation is 0.2332. As for investors' risk profiles, the results demonstrate a mean value of 0.3333 for each of the conservative, moderate and aggressive investors' risk profiles. Among all the variables, the number of portfolios offered displays the highest average value of 9.4898. The average value for expertise in equity class is 0.5188, while expertise in fixed income class is 0.3033. Turning to the macroeconomic variables, the average value for inflation rate is 0.0339, while exchange rate is 0.2300. Table 4 shows that on average, the portfolio recommendations for conservative investors are mainly made up of fixed income assets (0.6264), while the portfolio recommendations for moderate and aggressive investors primarily consist of equity assets, i.e., moderate (0.4431) and aggressive (0.6633).

Table 3 Descriptive statistics for all variables

Variable	*Observations*	*Mean*	*Std. dev.*	*Min*	*Max*
EQU	147	0.4511	0.2332	0.0000	1.0000
CONSE	147	0.3333	0.4730	0.0000	1.0000
MODER	147	0.3333	0.4730	0.0000	1.0000
AGGRE	147	0.3333	0.4730	0.0000	1.0000
PORTF	147	9.4898	7.8333	3.0000	38.0000
EQEXP	147	0.5188	0.1322	0.1939	0.8932
FIEXP	147	0.3033	0.1250	0.0028	0.5556
INFLR	147	0.0339	0.0163	0.0177	0.0701
EXCHR	147	0.2300	0.2824	0.0008	0.7407

Note: Refer to Table 2 for symbol and definitions of variables.

Table 4 Descriptive statistics for portfolio recommendations

Portfolio recommendations	*Observations*	*Mean*	*Std. dev.*	*Min*	*Max*
Conservative					
Equity	49	0.2470	0.1416	0.0000	0.7000
Fixed income	49	0.6264	0.1877	0.0915	0.9840
Others	49	0.1266	0.1602	0.0000	0.7678
Moderate					
Equity	49	0.4431	0.1466	0.0000	0.7850
Fixed income	49	0.4139	0.1489	0.0000	0.6202
Others	49	0.1430	0.1976	0.0000	1.0000
Aggressive					
Equity	49	0.6633	0.1880	0.1508	1.0000
Fixed income	49	0.2232	0.1220	0.0000	0.6149
Others	49	0.1136	0.1593	0.0000	0.7491

Table 5 Pearson correlation matrix

Variable	*EQU*	*CONSE*	*MODER*	*AGGRE*	*PORTF*	*EQEXP*	*FIEXP*	*INFLR*	*EXCHR*
EQU	1.0000								
CONSE	–0.6210*	1.0000							
MODER	–0.0244	–0.5000*	1.0000						
AGGRE	0.6454*	–0.5000*	–0.5000*	1.0000					
PORTF	0.0928	0.0000	–0.0000	–0.0000	1.0000				
EQEXP	0.0007	0.0043	–0.0002	–0.0041	0.5574*	1.0000			
FIEXP	0.0509	0.0023	–0.0001	–0.0022	–0.3113*	–0.2738*	1.0000		
INFLR	–0.0416	0.0000	0.0000	0.0000	0.3290*	0.3030*	–0.2793*	1.0000	
EXCHR	–0.0825	0.0000	–0.0000	–0.0000	0.5312*	0.4094*	–0.1322	0.4262*	1.0000

Notes: Refer to Table 2 for symbol and definitions of variables. An * represents statistical significance at the level of 5% or less.

Table 5 presents the Pearson correlation matrix. Since the independent variables exhibit relatively low correlation coefficients (i.e., below 0.8), this indicates that no multi-collinearity problem prevails. This is further supported by the low variance inflation factor value for all independent variables, i.e., below two (Gujarati and Porter, 2009).

4.2 Regression results

Table 6 presents the estimation results for the determinants of asset allocation decisions of robo-advisors. Standard errors are adjusted for heteroscedasticity and clustered by firms and years. The adjusted *R*-squared values for columns 1 through 3 range between 0.5750 and 0.5824, which offer a good indication of the models' predictive ability.

The analysis begins by estimating the association between investors' risk profiles and robo-advisors' asset allocation decisions (column 1). The findings reveal that the relationship between each of the investors' risk profiles and percentage of equity in the recommended portfolio is significantly positive at the 1% level, thus H1 is supported. Furthermore, the proportion of equity for aggressive investors tends to increase by 41.63%, whereas moderate and conservative (constant term) investors are recommended with a lesser equity portion, i.e., 19.61% and 16.67%, respectively. The results indicate that more risk-seeking profiles result in a higher proportion of equity allocation as compared to more risk-averse profiles.

Table 6 Regression results

Variable	*(1)*	*(2)*	*(3)*
Constant	0.1667*** (4.84)	0.1395 (1.34)	0.5335 (0.72)
MODER	0.1961*** (7.23)	0.1961*** (7.29)	0.1961*** (7.34)
AGGRE	0.4163*** (12.92)	0.4163*** (13.10)	0.4162*** (12.97)
PORTF		0.0048** (1.99)	0.0046* (1.75)
EQEXP		–0.0111 (–0.07)	–0.0131 (–0.09)
FIEXP		0.0139 (0.10)	–0.0248 (–0.16)
INFLR			–1.2102 (–0.75)
EXCHR			–1.5785 (–0.50)
Country effects	Yes	Yes	Yes
Observations	147	147	147
Adjusted *R*-squared	0.5750	0.5824	0.5786

Notes: Figures in parentheses are t-statistics. Standard errors are adjusted for heteroscedasticity and clustered by firms and years. Refer to Table 2 for symbol and definitions of variables. ***, **, * statistical significance at the level of 1%, 5% and 10%, respectively.

The findings lend credence to the MPT which posits that the optimal portfolios should match the investors' risk profiles with the expected returns while gaining diversification benefits. The results are also consistent with Boreiko and Massarotti (2020) who report a significant relationship between investors' risk profiles and percentage of equity in the recommended portfolio. The authors affirm that robo-advisors are able to recognise different investors' risk profiles and offer the optimal portfolio recommendations accordingly by allocating more share of equity to risk-seeking investors. Besides, the findings are in line with Scherer and Lehner (2021) who examine the relationship between investor characteristics and robo-advisors' asset allocation decisions. They report that aggressive investors are given higher allocation in equities by the robo-advisors. Similar evidence is provided by Tertilt and Scholz (2018) who assert that robo-advisors reflect the investors' risk profiles in their portfolio recommendations, where aggressive investors are recommended with riskier portfolios containing a higher share of equities. However, the findings are in contrast with Helms et al. (2022) who claim that a wide difference prevails in the portfolio recommendations given by the robo-advisors in each risk class in terms of risk-return trade-offs. In other words, robo-advisors do not follow standardised investment strategies for all the risk classes and their recommendations depend on the individual robo-advisors.

Next, we introduce fund characteristics into the regression model (column 2). The findings demonstrate that the association between the number of portfolios offered and percentage of equity in the recommended portfolio is significantly positive at the 5% level, which is in agreement with H2a. This indicates that variations in the number of model portfolios offered across robo-advisors enable the system to match the customer risk profile to an ideal portfolio, leading to different portfolio recommendations. Put differently, robo-advisors categorise investors into different risk profiles according to the responses given in the online risk assessment questionnaires and these risk profiles are usually associated with the number of standardised portfolios. Nevertheless, the findings are in contrast with Boreiko and Massarotti (2020) who report that the recommendations of robo-advisors are not associated with the number of portfolios offered. Likewise, Tertilt and Scholz (2018) also find that the relationship between the number of portfolios offered and quality of portfolio recommendations is statistically insignificant.

Turning to robo-advisors' expertise in different asset classes, the coefficient of expertise in equity class is negative but not statistically significant. Similarly, the coefficient of expertise in fixed income class is positive but statistically insignificant. Taken together, the findings suggest that H2b is not supported. The results indicate that the robo-advisors' portfolio recommendations are not influenced by the need to exploit economies of scale by concentrating on a limited number of asset classes in which they have expertise in. The findings are consistent with Manurung and Sihombing (2023) who report that economies of scale, measured by mutual fund size, is not a significant determinant of the performance of equity funds in Indonesia. By the same token, the results are in line with Christiandi and Colline (2021) who find that the size of equity funds is not significantly associated with their performance. Nonetheless, the results are not in accord with Boreiko and Massarotti (2020) who report a significant relationship between expertise in different asset classes, in particular equity and fixed income, and percentage of equity in the recommended portfolio. The authors claim that robo-advisors focus on the asset classes in which they have expertise in to achieve economies of scale.

Finally, we incorporate macroeconomic factors into the estimation model (column 3). The coefficient of inflation rate is negative but statistically insignificant, thus H3a is not supported. Similarly, the relationship between exchange rate and percentage of equity in the recommended portfolio is negative but statistically insignificant, which do not lend support to H3b. Collectively, the results suggest that robo-advisors in the Asia-Pacific region take into consideration investors' risk profiles and certain fund characteristics when developing portfolio recommendations but not macroeconomic factors.

4.3 Further analysis: results for each investor style

Table 7 tabulates the regression results of each investor's risk profile separately. The coefficient of the number of portfolios offered is significantly positive at the 10% level for aggressive investors, which provides further support to H2a. This indicates that the breadth of portfolio choices serves a critical role in determining the robo-advisors' portfolio recommendations, especially for aggressive investors.

Table 7 Results for each investor style

Variable	*Conservative*	*Moderate*	*Aggressive*
Constant	0.5206 (0.76)	1.6887 (1.35)	–0.0018 (–0.00)
PORTF	0.0024 (0.70)	0.0025 (0.70)	0.0086* (1.90)
EQEXP	–0.0258 (–0.14)	–0.0154 (–0.08)	0.0140 (0.04)
FIEXP	–0.3925** (–2.13)	–0.1225 (–0.55)	0.4480 (1.37)
INFLR	–3.2962* (–1.88)	–3.1180 (–1.18)	2.8492 (0.82)
EXCHR	–0.5571 (–0.18)	–5.5757 (–1.04)	1.3808 (0.19)
Country effects	Yes	Yes	Yes
Observations	49	49	49
Adjusted R-squared	0.1951	0.0263	–0.0222

Notes: Figures in parentheses are t-statistics. Standard errors are adjusted for heteroscedasticity and clustered by firms and years. Refer to Table 2 for symbol and definitions of variables. ***, **, * statistical significance at the level of 1%, 5% and 10%, respectively.

Interestingly, the coefficient of expertise in fixed income class becomes significantly negative at the 5% level for conservative investors, which is in agreement with H2b. This implies that robo-advisors are motivated to exploit economies of scale to remain price competitive by allocating the investors' portfolios in a limited number of financial products or asset classes in which they have expertise in. Specifically, robo-advisors with more expertise in fixed income class tend to allocate more in fixed income assets and less in equities in their recommended portfolios for conservative investors.

Similar evidence is documented by Choi et al. (2016) who report that investment firms allocate resources, including income streams, in favour of funds with higher economic values to enjoy scale benefits. Along the same lines, Boreiko and Massarotti (2020) find that robo-advisors' expertise in certain asset classes plays an important role in influencing their asset allocation decisions, where robo-advisors with more expertise in fixed income assets tend to allocate more of these financial products in their recommended portfolios.

The coefficient of inflation rate also turns significantly negative at the 10% level for conservative investors, which is in line with H3a. This suggests that robo-advisors tend to allocate less in equities in their recommended portfolios for conservative investors during periods of high inflation. The result corroborates the findings by Brière and Signori (2009) who assert that conservative investors should predominantly hold cash for the short-term during uncertain economic conditions such as high inflation to hedge against inflation risk. The finding is also consistent with Shao et al. (2023) who reveal that greater expected inflation rate will result in less proportion being invested in stocks.

Meanwhile, the relationship between exchange rate and percentage of equity in the recommended portfolio is consistently not statistically significant in both Tables 6 and 7. This could be due to robo-advisors holding internationally diversified portfolios which enable them to diversify their exchange rate exposures and risks across different asset classes and markets (Rossi and Utkus, 2024). This further implies that robo-advisors do not need to rebalance their portfolios across different asset classes to hedge against any movements in exchange rates.

5 Robustness tests

To assess the sensitivity of the empirical findings, we re-estimate the regression models by incorporating an alternative proxy for expertise in different asset classes, i.e., expertise in other asset classes (*OAEXP*), measured as the weightage of other asset classes (besides equity and fixed income) in the robo-advisors' investment universe. As outlined in Table 8, column 1 incorporates only one proxy for expertise in different asset classes, i.e., expertise in other asset classes. Next, column 2 includes two proxies, i.e., expertise in equity class and expertise in other asset classes. Similarly, column 3 also adopts two proxies, i.e., expertise in fixed income class and expertise in other asset classes. In all three specifications, the coefficient of expertise in other asset classes is not statistically significant. Meanwhile, the results for other variables are qualitatively similar to those tabulated in Table 6, thus reaffirming the central findings' robustness.

Table 8 Robustness: regression results with expertise in other asset classes

Variable	*(1)*	*(2)*	*(3)*
Constant	0.5102 (0.71)	0.5087 (0.70)	0.5204 (0.72)
MODER	0.1961*** (7.36)	0.1961*** (7.34)	0.1961*** (7.34)
AGGRE	0.4162*** (13.02)	0.4162*** (12.97)	0.4162*** (12.97)
PORTF	0.0046** (2.29)	0.0046* (1.75)	0.0046* (1.75)
EQEXP		0.0117 (0.06)	
FIEXP			–0.0117 (–0.06)
OAEXP	0.0188 (0.16)	0.0248 (0.16)	0.0131 (0.09)
INFLR	–1.1863 (–0.77)	–1.2103 (–0.75)	–1.2102 (–0.75)
EXCHR	–1.5585 (–0.49)	–1.5787 (–0.50)	–1.5786 (–0.50)
Country effects	Yes	Yes	Yes
Observations	147	147	147
Adjusted R-squared	0.5817	0.5786	0.5786

Notes: Figures in parentheses are t-statistics. Standard errors are adjusted for heteroscedasticity and clustered by firms and years. Refer to Table 2 for symbol and definitions of variables. ***, **, * statistical significance at the level of 1%, 5% and 10%, respectively.

6 Concluding remarks

6.1 Conclusions

This paper investigates the determinants of asset allocation decisions of robo-advisors based on a sample of 30 robo-advisors in seven Asia-Pacific economies over the period 2022 to 2024. The results reveal that investors' risk profiles exert a significant positive effect on the percentage of equity in the recommended portfolio. In particular, risk-seeking investors are allocated with more equities than risk-averse investors. In terms of fund characteristics, we demonstrate that the number of portfolios offered has a significant positive influence on the percentage of equity, especially for aggressive investors, which implies that variations in the number of model portfolios offered across robo-advisors result in different portfolio recommendations. On the flip side, expertise in fixed income class exerts a significant negative effect on the percentage of equity in the recommended portfolio, particularly for conservative investors. Lastly, macroeconomic factors, in particular inflation rate, negatively affect the percentage of equity in the recommended portfolio of conservative investors.

6.2 Theoretical implications

Theoretically, the results lend credence to the MPT in offering theoretical justifications for considering investors' risk attitudes in generating the optimal portfolios. Although numerous studies have applied the MPT in the construction of portfolios, they solely focus on human practices (Kaplan and Siegel, 2011; Ünlü and Xanthopoulos, 2021). Hence, this study enriches our understanding on how the MPT can be applied in automation or machine learning ability of algorithm systems in recommending the ideal portfolios that are in accordance with the investors' risk attitudes and expected returns while gaining diversification benefits.

Besides, this research broadens the literature on robo-advisors, particularly the determinants of their asset allocation decisions. Extant studies on the determinants of asset allocation decisions have predominantly focused on human advisors but there is a paucity of studies which have explored robo-advisors. Specifically, past literature has revealed that there is an association between investors' risk attitude and personal characteristics and the asset allocation decisions of human advisors or investors (Cavezzali and Rigoni, 2012; Zhang et al., 2018). There are, however, rather limited studies which explore the relationship between investors' risk profiles and robo-advisors' asset allocation decisions (Boreiko and Massarotti, 2020; Scherer and Lehner, 2021). Besides, these papers only concentrate on Western countries, especially the USA. Nonetheless, very little is known about how the asset allocation decisions are generated by these digital platforms, particularly in the Asia-Pacific context, since robo-advisor is a relatively new FinTech concept in this region as compared to Western developed countries.

Furthermore, this paper contends that fund characteristics may also affect robo-advisors' asset allocation decisions. Thus far, fund characteristics have predominantly been examined from the fund performance perspective (Choi et al., 2016; Joenväärä et al., 2021) but there is a dearth of research on how fund characteristics relate to the asset allocation decisions by either human or robo-advisors (Boreiko and Massarotti, 2020; Tertilt and Scholz, 2018). Moreover, extant literature has documented the impact of macroeconomic factors on the performance of different asset classes and investors' asset allocation decisions (Ilmanen et al., 2014; Shao et al., 2023; Sheikh and Sun, 2012). Even though the majority of robo-advisors claim that they rebalance the portfolio weights according to market conditions, these platforms do not publish the adjustment algorithms (Helms et al., 2022). To date, very few studies have considered the effect of macroeconomic factors on robo-advisors' asset allocation decisions (Ahn et al., 2020; Gu et al., 2019). Therefore, this study enriches the literature by furnishing insightful findings on how investors' risk profiles, fund characteristics and macroeconomic factors influence the robo-advisors' asset allocation decisions based on Asia-Pacific economies.

6.3 Practical implications

In terms of practical implications, the findings may provide valuable guidance to policymakers to enact better policies and regulations in supervising robo-advisors and evaluating their algorithms as well as protecting investors' rights by making these algorithm systems more interpretable. For example, given that robo-advisory involves new technology for providing investment advisory services and there is a growing demand for these services, these developments create the need for greater transparency and interpretability in the process involved in generating the portfolio recommendations. Presently, one of the major criticisms of robo-advisors is there is lack of interpretability and transparency on how these platforms develop portfolio recommendations because the algorithm systems used for analysing, matching and recommending the portfolios are unpublished or unknown (Kato, 2020; Molnar, 2020; Torno et al., 2021). Resultantly, this lack of reasoning behind the process involved in the robo-advisors' asset allocation decisions renders building a long-term trust-based relationship with the investors very challenging. Hence, policymakers may want to consider enforcing legal requirements for robo-advisors to disclose a detailed statement on the rationale for their asset allocation and rebalancing recommendations such as whether these choices are driven by the investors' risk profiles, fund characteristics or macroeconomic factors to establish better trust in this advisory service. In this manner, investors can have a better picture about their tolerance and limits towards the recommended investment products as well as have better estimation of the risks associated with these products (Shanmuganathan, 2020). Additionally, policymakers should carefully monitor their inflation rates which may adversely affect robo-advisors' asset allocation decisions.

Furthermore, this research may prompt system developers of robo-advisor platforms to review and redesign an enhanced algorithm system, where the risk assessment questionnaires should be unambiguous, comprehensive and relevant, and the information collected should be fully reflected in the portfolio recommendations. This is to ensure that these platforms develop a more accurate understanding of the investors' risk preferences and the portfolio recommendations offered should be in line with these risk preferences. Stated differently, the portfolio recommendations made by the robo-advisors are according to the algorithms derived from the answers furnished by the investors in the online questionnaires. Thereby, robo-advisors have to ensure that compatibility and logic of the decision-making algorithms are in place (Shanmuganathan, 2020). In order to further ensure the accuracy of clients' information, robo-advisors may introduce a third-party information verification function and practice proper record tracing and management to retain records and gather real-time information updates (Guo, 2020). Moreover, fund characteristics such as the number of model portfolios offered and expertise in different asset classes should be carefully monitored because they may lead to variations in portfolio recommendations. Besides, these algorithm systems should be regularly adjusted to reflect the latest economic environment, especially with regards to changes in inflation rates.

Finally, this study may provide better insights to individual investors or the society at large on how robo-advisors derive their portfolio recommendations and what information they depend on. This may assist them to formulate rational and informed investment decisions by better comprehending the underlying factors influencing the asset allocation and rebalancing recommendations by the robo-advisors. For instance, investors have to fill up the risk assessment questionnaires carefully and truthfully because their risk profiles have a significant impact on robo-advisors' asset allocation decisions. Moreover, investors should pay close attention to fund characteristics such as the number of model portfolios offered and expertise in different asset classes as well as scrutinise developments in the economic environment such as inflation rate movements, which may have a significant bearing on the robo-advisors' asset allocation decisions.

6.4 Limitations and future research

Several limitations should be highlighted in this paper. First, this study is unable to incorporate all active robo-advisors in the seven Asia-Pacific economies because of data availability issues. This problem is also highlighted by other researchers such as Boreiko and Massarotti (2020) who could not include all active platforms in Germany and the USA due to various restrictions. Nevertheless, the current study asserts that we have identified and incorporated in our sample all platforms where data are publicly accessible. The second limitation is this research is limited to seven economies in Asia Pacific. Future research may include more sample countries to enhance the generalisability of the findings.

References

Ahmed, W.M.A. (2020) 'Asymmetric impact of exchange rate changes on stock returns: evidence of two de facto regimes', *Review of Accounting and Finance*, Vol. 19, No. 2, pp.147–173.

Ahn, W., Lee, H.S., Ryou, H. and Oh, K.J. (2020) 'Asset allocation model for a robo-advisor using the financial market instability index and genetic algorithms', *Sustainability*, Vol. 12, No. 3, pp.1–15.

Alserda, G.A.G., Dellaert, B.G.C., Swinkels, L. and Lecq, F.S.G.V.D. (2019) 'Individual pension risk preference elicitation and collective asset allocation with heterogeneity', *Journal of Banking & Finance*, Vol. 101, pp.206–225.

Atmaningrum, S., Kanto, D.S. and Kisman, Z. (2021) 'Investment decisions: the results of knowledge, income, and self-control', *Journal of Economics and Business*, Vol. 4, No. 1, pp.100–112.

Aw, E.C.X., Leong, L.Y., Hew, J.J., Rana, N.P., Tan, T.M. and Jee, T.W. (2024) 'Counteracting dark sides of robo-advisors: justice, privacy and intrusion considerations', *International Journal of Bank Marketing*, Vol. 42, No. 1, pp.133–151.

Baker, H.K. and Ricciardi, V. (2014) *Investor Behavior: The Psychology of Financial Planning and Investing*, John Wiley & Sons, New Jersey.

Baruah, M. and Parikh, A.K. (2018) 'Impact of risk tolerance and demographic factors on financial investment decision', *International Journal of Financial Management*, Vol. 8, No. 1, pp.36–48.

Belanche, D., Casaló, L.V. and Flavián, C. (2019) 'Artificial intelligence in FinTech: understanding robo-advisors adoption among customers', *Industrial Management & Data Systems*, Vol. 119, No. 7, pp.1411–1430.

Bhatia, A., Chandani, A., Divekar, R., Mehta, M. and Vijay, N. (2022) 'Digital innovation in wealth management landscape: the moderating role of robo advisors in behavioural biases and investment decision-making', *International Journal of Innovation Science*, Vol. 14, Nos. 3/4, pp.693–712.

Boreiko, D. and Massarotti, F. (2020) 'How risk profiles of investors affect robo-advised portfolios', *Frontiers in Artificial Intelligence*, Vol. 3, No. 60, pp.1–9.

Brenner, L. and Meyll, T. (2020) 'Robo-advisors: a substitute for human financial advice?', *Journal of Behavioral and Experimental Finance*, Vol. 25, p.100275.

Brière, M. and Signori, O. (2009) *Inflation-Hedging Portfolios in Different Regimes*, Solvay Brussels School of Economics and Management Centre Emile Bernheim Working Paper, No. 09/047, Brussels.

Budig, M.J. and England, P. (2001) 'The wage penalty for motherhood', *American Sociological Review*, Vol. 66, No. 2, pp.204–225.

Camanho, N., Hau, H. and Rey, H. (2022) 'Global portfolio rebalancing and exchange rates', *The Review of Financial Studies*, Vol. 35, No. 11, pp.5228–5274.

Cavezzali, E. and Rigoni, U. (2012) 'Know your client! Investor profile and tailor-made asset allocation recommendations', *The Journal of Financial Research*, Vol. 35, No. 1 pp.137–158.

Census and Statistics Department (2021) *Labour Force, Employment and Unemployment* [online] https://www.censtatd.gov.hk/en/scode200.html (accessed 2 March 2022).

Chang, V., Ni, L., Zhang, J. and Li, T. (2020) 'The current trends and overview for portfolio management', *International Journal of Business and Systems Research*, Vol. 14, No. 4, pp.434–454.

Choi, D., Li, X., Yao, T. and Zhang, Z. (2016) *All in the Family: Economies of Scale in Retail and Institutional Investment Management*, Institutional Knowledge Lee Kong Chian School of Business Working Paper, No. 12-2016, Singapore.

Chow, E.H., Lee, W.Y. and Solt, M.E. (1997) 'The exchange-rate risk exposure of asset returns', *The Journal of Business*, Vol. 70, No. 1, pp.105–123.

Christiandi, S. and Colline, F. (2021) 'Pengaruh inflasi, ukuran, dan umur terhadap kinerja reksa dana saham di Indonesia', *Jurnal Administrasi Bisnis*, Vol. 17, No. 2, pp.194–205.

Christiansen, C., Joensen, J.S. and Rangvid, J. (2015) 'Understanding the effects of marriage and divorce on financial investments: the role of background risk sharing', *Economic Inquiry*, Vol. 53, No. 1, pp.431–447.

Corter, J.E. and Chen, Y.J. (2006) 'Do investment risk tolerance attitudes predict portfolio risk', *Journal of Business and Psychology*, Vol. 20, No. 3, pp.369–381.

Damodaran, A. (2012) *Investment Philosophies: Successful Strategies and the Investors who Made Them Work*, John Wiley & Sons, New Jersey.

Department of Statistics Malaysia (2017) *Employment by Sector* [online] https://www.ilmia.gov.my/index.php/en/dashboard-datamart/kilm/indicators/item/employment-by-sector (accessed 2 March 2022).

Department of Statistics Malaysia (2021) *Current Population Estimates*, Malaysia [online] https://www.dosm.gov.my/v1/index.php?r=column/cthemeByCat&cat=155&bul_id=ZjJOSnpJR21sQWVUcUp6ODRudm5JZz09&menu_id=L0pheU43NWJwRWVSZklWdzQ4TlhUUT09 (accessed 2 March 2022).

Department of Statistics Singapore (2022) *Population and Population Structure* [online] https://www.singstat.gov.sg/find-data/search-by-theme/population/population-and-population-structure/latest-data (accessed 2 March 2022).

Dhume, S. (2021) *India May Face a Population Implosion* [online] https://www.wsj.com/articles/india-may-face-a-population-implosion-fertility-rate-replacement-levels-children-11640289956 (accessed 10 March 2022).

Fan, L. and Chatterjee, S. (2020) 'The utilization of robo-advisors by individual investors: an analysis using diffusion of innovation and information search frameworks', *Journal of Financial Counseling and Planning*, Vol. 31, No. 1, pp.130–145.

FinTech News Hong Kong (2022) *FinTech News Hong Kong* [online] https://fintechnews.hk (accessed 14 June 2022).

Gakhar, D.V. and Prakash, D. (2017) 'Investment behaviour: a study of relationship between investor biases and Myers Briggs type indicator personality', *Organization People & US: Human Resources Journal*, Vol. 8, No. 1, pp.32–60.

Gauthier, A.H. and de Jong, P.W. (2021) 'Costly children: the motivations for parental investment in children in a low fertility context', *Genus*, Vol. 77, No. 6, pp.1–19.

Gerhana, Y.A., Umam, M.M. and Atmadja, A.R. (2021) 'Implementation of the Markowitz method in the robo-advisor application for best investment selection', *IOP Conference Series: Materials Science and Engineering*, Vol. 1098, No. 3, p.032051.

Giesselmann, M. and Schmidt-Catran, A.W. (2019) 'Getting the within estimator of cross-level interactions in multilevel models with pooled cross-sections: why country dummies (sometimes) do not do the job', *Sociological Methodology*, Vol. 49, No. 1, pp.190–219.

Grable, J.E., Joo, S.H. and Kruger, M. (2020) 'Risk tolerance and household financial behaviour: a test of the reflection effect', *IIMB Management Review*, Vol. 32, No. 4, pp.402–412.

Greninger, S.A., Hampton, V.L., Kitt, K.A. and Achacoso, J.A. (1996) 'Ratios and benchmarks for measuring the financial well-being of families and individuals', *Financial Services Review*, Vol. 5, No. 1, pp.57–70.

Gu, C.S., Hsieh, H.P., Wu, C.S., Chang, R.I and Ho, J.M. (2019) 'A fund selection robo-advisor with deep-learning driven market prediction', *2019 IEEE International Conference on Systems, Man and Cybernetics*, pp.2845–2850.

Gujarati, D.N. and Porter, D.C. (2009) *Basic Econometrics*, McGraw-Hill, New York.

Guo, L. (2020) 'Regulating investment robo-advisors in China: problems and prospects', *European Business Organization Law and Review*, Vol. 21, pp.69–99.

Helms, N., Hölscher, R. and Nelde, M. (2022) 'Automated investment management: comparing the design and performance of international robo-managers', *European Financial Management*, Vol. 28, No. 4, pp.1028–1078.

Hickman, K., Hunter, H., Byrd, J., Beck, J. and Terpening, W. (2001) 'Life cycle investing, holding periods, and risk', *The Journal of Portfolio Management*, Vol. 27, No. 2, pp.101–111.

Hyll, W. and Irrek, M. (2015) *The Impact of Risk Attitudes on Financial Investments*, Halle Institute for Economic Research Discussion Papers, No. 10/2015, Germany.

Ilmanen, A., Maloney, T. and Ross, A. (2014) 'Exploring macroeconomic sensitivities: how investments respond to different economic environments', *The Journal of Portfolio Management*, Vol. 40, No. 3, pp.87–99.

International Monetary Fund (2020) *Japan: Demographic Shift Opens Door to Reforms* [online] https://www.imf.org/en/News/Articles/2020/02/10/na021020-japan-demographic-shift-opens-door-to-reforms (accessed 10 March 2022).

Joenväärä, J., Kaupilla, M. and Kahra, H. (2021) 'Hedge fund portfolio selection with fund characteristics', *Journal of Banking & Finance*, Vol. 132, p.106232.

Junaid, Z.B., Siddique, M. and Baig, M. (2020) 'Optimizing the risk & return of Shanghai Stock Exchange for European markets: application of modern portfolio theory', *Journal of European Studies*, Vol. 36, No. 2, pp.100–115.

Kaplan, P.D. and Siegel, L.B. (2011) *Frontiers of Modern Asset Allocation*, John Wiley & Sons, New Jersey.

Kato, Y. (2020) 'AI/FinTech and asset management businesses', *Public Policy Review*, Vol. 16, No. 4, pp.1–28.

Kim, S., Cotwright, M. and Chatterjee, S. (2019) 'Who are robo-advisor users?', *Journal of Finance Issues*, Vol. 18, No. 2, pp.33–50.

Kim, W.C., Kwon, D.G., Lee, Y., Kim, J.H. and Lin, C. (2020) 'Personalized goal-based investing via multi-stage stochastic goal programming', *Quantitative Finance*, Vol. 20, No. 3, pp.515–526.

Koniarski, T. and Sebastian, S. (2015), 'Inflation-protecting asset allocation: a downside risk analysis', *The Journal of Portfolio Management*, Vol. 41, No. 2, pp.57–70.

Korean Statistical Information Service (2022) *Population Projections* [online] https://kosis.kr/statHtml/statHtml.do?orgId=101&tblId=DT_1BPA002&language=en (accessed 10 March 2022).

KPMG (2021) *Digital Wealth Management in Asia Pacific* [online] https://assets.kpmg/content/dam/kpmg/cn/pdf/en/2021/03/digital-wealth-management-in-asia-pacific.pdf (accessed 12 March 2022).

Li, L. (2002) *Macroeconomic Factors and the Correlation of Stock and Bond Returns*, Yale International Center for Finance Working Paper, No. 02-46, Connecticut.

Liu, C., Yang, M. and Wen, M.H. (2021) *Judge Me on My Losers: Does Adaptive Robo-Advisors Outperform Human Investors during the COVID-19 Financial Market Crash?* [online] https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3737821 (accessed 1 May 2022).

Lutfi, L. (2010) 'The relationship between demographic factors and investment decision in Surabaya', *Journal of Economics, Business and Accountancy Ventura*, Vol. 13, No. 3, pp.213–224.

Manurung, A.H. and Sihombing, P. (2023) 'The impact of stock selection, market timing and equity fund size on equity funds performance during COVID-19', *Kontigensi: Jurnal Ilimiah Manajemen*, Vol. 11, No. 1, pp.194–201.

Markowitz, H. (1952) 'Portfolio selection', *The Journal of Finance*, Vol. 7, No. 1, pp.77–91.

Ministry of Education Malaysia (2020) *Laporan Tahunan 2020* [online] https://www.moe.gov.my/menumedia/media-cetak/penerbitan/pppm-2013-2025-pendidikan-prasekolah-hingga-lepas-menengah/4600-laporan-tahunan-pppm-2020/file (accessed 10 March 2022).

Ministry of Education of the Republic of China (Taiwan) (2021) *Enrolment Rates of School – Net Enrolment Rates* [online] https://stats.moe.gov.tw/files/ebook/indicators/13.pdf (accessed 10 March 2022).

Ministry of Manpower (2022) *Summary Table: Employment* [online] https://stats.mom.gov.sg/Pages/Employment-Summary-Table.aspx (accessed 2 March 2022).

Ministry of the Interior (2021) *Population by Single Year of Age and Median Age* [online] https://ws.moi.gov.tw/001/Upload/OldFile/site_stuff/321/1/month/month_en.html (accessed 10 March 2022).

Molnar, C. (2020) *Interpretable Machine Learning: A Guide for Making Black Box Models Explainable*, Lean Publishing, Canada.

Muganda, B.W. and Kasamani, B.S. (2023) 'Parallel programming for portfolio optimization: a robo-advisor prototype using genetic algorithms with recurrent neural networks', *2023 International Conference on Intelligent Computing, Communication, Networking and Services*, pp.167–176.

Nain, I. and Rajan, S. (2023) 'Algorithms for better decision-making: a qualitative study exploring the landscape of robo-advisors in India', *Managerial Finance*, Vol. 49, No. 11, pp.1750–1761.

Namango, I.M. (2018) 'Macroeconomic factors and the correlation of stock and bond returns: empirical evidence from Kenya', *Advances in Social Sciences Research Journal*, Vol. 5, No. 8, pp.349–378.

National Statistics of Republic of China (Taiwan) (2022) *Employed Persons by Occupation* [online] https://eng.stat.gov.tw/ct.asp?xItem=12683&ctNode=1609 (accessed 2 March 2022).

Phoa (2023) 'Strategic asset allocation and inflation resilience', *The Journal of Portfolio Management*, Vol. 49, No. 4, pp.45–63.

Population Census (2021) *Summary Results of 2021 Population Census* [online] https://www.census2021.gov.hk/en/media.html (accessed 10 March 2022).

Profesia (2022) *Worldwide Salaries* [online] https://www.paylab.com (accessed 2 May 2022).

Puhle, M. (2019) 'The performance and asset allocation of German robo-advisors', *Society and Economy*, Vol. 41, No. 3, pp.331–351.

Ramudzuli, P.M. and Muzindutsi, P.F. (2018) 'Determinants of financial and non-financial risk tolerance among students at selected South African universities', *Foundations of Management*, Vol. 10, No. 1, pp.293–302.

Ritchie, H. and Roser, M. (2019) *Age Structure* [online] https://ourworldindata.org/age-structure (accessed 10 March 2022).

Roh, T., Park, B. and Xiao, S. (2023) 'Adoption of AI-enabled robo-advisors in FinTech: simultaneous employment of UTAUT and the theory of reasoned action', *Journal of Electronic Commerce Research*, Vol. 24, No. 1, pp.29–47.

Rossi, A.G. and Utkus, S. (2024) 'The diversification and welfare effects of robo-advising', *Journal of Financial Economics*, Vol. 157, p.103869.

Sabir, A.A., Ahmad, I., Ahmad, H., Rafiq, M., Khan, M.A. and Noreen, N. (2023) 'Consumer acceptance and adoption of AI robo-advisors in FinTech industry', *Mathematics*, Vol. 11, No. 6, p.1311.

Scherer, B. and Lehner, S. (2021) *What Drives Robo-Advice?* [online] https://climateimpact.edhec.edu/publications/what-drives-robo-advice (accessed 14 March 2022).

Shanmuganathan, M. (2020) 'Behavioural finance in an era of artificial intelligence: longitudinal case study of robo-advisors in investment decisions', *Journal of Behavioral and Experimental Finance*, Vol. 27, p.100297.

Shao, Y., Xia, D. and Fei, W. (2023) 'Optimal investment strategy for DC pension plan with inflation risk under the hybrid stochastic volatility model', *Systems Science & Control Engineering*, Vol. 11, No. 1, p.2186962.

Shefrin, H. and Statman, M. (2000) 'Behavioral portfolio theory', *The Journal of Financial and Quantitative Analysis*, Vol. 35, No. 2, pp.127–151.

Sheikh, A.Z. and Sun, J. (2012) 'Regime change: implications of macroeconomic shifts on asset class and portfolio performance', *The Journal of Investing*, Vol. 21, No. 3, pp.36–54.

Sironi, P. (2016) *FinTech Innovation: From Robo-Advisors to Goal Based Investing and Gamification*, John Wiley & Sons, Chichester.

Stanley, T.J. and Danko, W.D. (1996) *The Millionaire Next Door: The Surprising Secrets of America's Wealthy*, Longstreet Press, Georgia.

Statista (2022) *Number of People Employed Across Major Sectors in India in Financial Year 2021* [online] https://www.statista.com/statistics/1283990/india-sector-wise-employment (accessed 10 March 2022).

Statistics Bureau of Japan (2022) *Monthly Results*, January [online] https://www.stat.go.jp/english/data/roudou/results/month/index.html (accessed 10 March 2022).

Statistics Korea (2022) *Characteristics of the Employed Persons by Industry and Occupation According to the Local Area Labour Force Survey in the First Half of 2021* [online] https://kostat.go.kr/portal/eng/pressReleases/5/1/index.board?bmode=download&bSeq=&aSeq=414852&ord=1 (accessed 10 March 2022).

Tertilt, M. and Scholz, P. (2018) 'To advise, or not to advise – how robo-advisors evaluate the risk preferences of private investors', *Journal of Wealth Management*, Vol. 21, No. 2, pp.70–84.

Thanki, H. and Baser, N. (2019), 'Interactive impact of demographic variables and personality type on risk tolerance', *Emerging Economy Studies*, Vol. 5, No. 1, pp.42–54.

Torno, A., Metzler, D.R. and Torno, V. (2021) 'Robo-what?, robo-why?, robo-how? – a systematic literature review of robo-advice', *Proceedings of the 25th Pacific Asia Conference on Information Systems*, pp.1–14.

United Nations Educational, Scientific and Cultural Organisation Institute for Statistics (2022) *Education and Literacy* [online] http://uis.unesco.org (accessed 10 March 2022).

Ünlü, R. and Xanthopoulos, P. (2021) 'A reduced variance unsupervised ensemble learning algorithm based on modern portfolio theory', *Expert Systems with Applications*, Vol. 180, p.115085.

Verdiyanto, R. (2020) 'An empirical implementation of Markowitz modern portfolio theory on Indonesia Sharia equity fund: a case of Bahana icon Syariah mutual fund', *Journal of Accounting and Finance in Emerging Economies*, Vol. 6, No. 4, pp.1159–1172.

Warren, E. and Tyagi, A.W. (2006) *All Your Worth: The Ultimate Lifetime Money Plan*, Free Press, New York.

Wong, H.T. (2017) 'Real exchange rate returns and real stock price returns', *International Review of Economics & Finance*, Vol. 49, pp.340–352.

World Bank Group (2022) *Long-term Finance* [online] https://www.worldbank.org/en/publication/gfdr/gfdr-2016/background/long-term-finance#:~:text=Long%2Dterm%20finance%20can%20be,public%20and%20private%20equity%20instruments (accessed 17 March 2022).

Xiao, S. and Adekola, T.A. (2021) 'Investment in robo-advisors: some reflections on China's regulatory experience', *Banking & Finance Law Review*, Vol. 37, No. 1, pp.127–148.

Zhang, A.C., Fang, J., Jacobsen, B. and Marshall, B.R. (2018) 'Peer effects, personal characteristics and asset allocation', *Journal of Banking & Finance*, Vol. 90, pp.76–95.

Zhang, L., Pentina, I. and Fan, Y. (2021) 'Who do you choose? Comparing perceptions of human vs robo-advisor in the context of financial services', *Journal of Services Marketing*, Vol. 35, No. 5, pp.628–640.

Appendix

Construction of investors' risk profiles

1 *Age:* Younger adults are typically more digitally-savvy, hence the probability of adopting robo-advisors is higher than older adults (Brenner and Meyll, 2020; Kim et al., 2019). The average age of robo-advisors' customers in Asia is unavailable. However, some studies contend that the acceptance and adoption of robo-advisors are the same across all age groups (Belanche et al., 2019; Fan and Chatterjee, 2020). As of 2021, the median age of the Malaysian population was 29.6 years (Department of Statistics Malaysia, 2021), Singapore was 41.8 years (Department of Statistics Singapore, 2022) and Hong Kong SAR was 46.23 years (Population Census, 2021). In the absence of information from the Indian government, Our World in Data (Ritchie and Roser, 2019) provides that the median age for India was 28.2 years for 2015 and according to The Wall Street Journal (Dhume, 2021), the median age for 2021 was 28. Since both ages are similar, 28 years is taken as the median age of the Indian population. The latest available median age for South Korea was for 2016 but the projection for 2021 was 44.3 years (Korean Statistical Information Service, 2022). For Taiwan and Japan, the median ages were 42.59 years (Ministry of the Interior, 2021) and 48.4 years (International Monetary Fund, 2020), respectively as of 2020. Accordingly, the average median age of these seven economies, i.e., approximately 40 years old, is applied in the construction of investors' profiles.

2 *Gender:* For the purpose of generalisation, we have chosen not to compare and differentiate between men and women, which is consistent with Boreiko and Massarotti (2020). Belanche et al. (2019) contend that gender does not influence the intention to use robo-advisors, where both men and women formulate similar adoption decisions. Similarly, Liu et al. (2021) demonstrate that there is no difference between male and female when it comes to the decision to adopt robo-advisors. Hence, for the sake of generalisation and consistency, this paper indicates male as the gender of the investor to fill up the online questionnaires on the robo-advisor platforms.

3 *Educational background or level:* Normally, individuals with higher educational level display greater risk tolerance and they may not be able to fulfil their risk appetite by following the investment advice provided by the robo-advisors. This can be attributed to the fact that individuals who have attained a high educational level are more capable of evaluating benefits and risks more carefully than those with lower educational level (Ramudzuli and Muzindutsi, 2018). Additionally, Atmaningrum et al. (2021) assert that the higher one's knowledge is in finance, the better is the problem-solving and decision-making ability in investing. This suggests that individuals with finance and investment educational backgrounds are more likely to manage their own portfolios.

In Malaysia, the upper secondary school enrolment rate as of 2020 was 87.6% (Ministry of Education Malaysia, 2020). According to the United Nations Educational, Scientific and Cultural Organisation Institute for Statistics (2022), the respective upper secondary school enrolment rates as of 2020 for India and Hong Kong SAR were 66% and 97.7%, while for Singapore, South Korea and Japan were 98.6%, 93% and 98.3% as of 2019. Meanwhile, Taiwan's upper secondary school enrolment rate was 94.06% as of 2020 [Ministry of Education of the Republic of China (Taiwan), 2021].

Since upper secondary school is the minimum qualification for the majority of population in the seven sample economies and secondary school courses are not specialised in the finance and investment areas, the upper secondary school qualification is chosen as the educational background or level in the construction of investors' profiles. This is equivalent to the Malaysia Certificate of Education in Malaysia, General Certificate of Education Ordinary Level in Singapore, Central Board of Secondary Education Class 12 board exam in India and Hong Kong Diploma of Secondary Education. For Taiwan, Japan and South Korea, students do not have to sit for any public examinations to graduate from secondary schools. Instead, they are required to attend a public entrance examination for tertiary studies.

4 *Occupation and experience:* Liu et al. (2021) elucidate that it is less likely for experienced investors to adopt robo-advisors because they have the relevant knowledge to construct their own portfolios. Besides, some employees of financial institutions are prohibited from investing via robo-advisors due to the restrictions imposed by their respective employers. Resultantly, we have decided to choose non-financial related middle-class workforce as the general occupation in the construction of investors' profiles.

The sales and service industry in Malaysia (Department of Statistics Malaysia, 2017) and Singapore (Ministry of Manpower, 2022) has the largest workforce for all working age groups. Meanwhile, the Census and Statistics Department (2021) of Hong Kong SAR reports that the service industry has the largest distribution of employment by industry. In Taiwan, the number of craft and operation related workers are the largest while the number of service and sales workers are the second largest in the market (National Statistics of Republic of China (Taiwan), 2022). Likewise, the service industry registered the second highest number of employments in India (Statista, 2022). The Statistics Bureau of Japan (2022) provides that the manufacturing sector as well as the wholesale and retail trade sector have the largest workforce in Japan. According to Statistics Korea (2022), the sales and service industry has the most employment. Hence, we choose 'sales and service personnel' as the general occupation in the construction of investors' profiles.

5 *Monthly income:* The median monthly income for the age group 35 to 44 years old was MYR3,791 (USD861.69) for Malaysia, SGD5,918 (USD4,275.16) for Singapore, INR36,773 (USD470.69) for India, HKD20,493 (USD2,610.81) for Hong Kong SAR, TWD53,000 (USD1,791.40) for Taiwan, JPY389,000 (USD2,917.50) for Japan and KRW3,900,000 (USD3,120) for South Korea (Profesia, 2022) based on the average exchange rate of USD per local currency as of June 2022. Accordingly, the average monthly income of the seven sample economies is USD2,292.46.

6 *Marital status:* Extant literature has documented that marital status affects investment behaviour (Baker and Ricciardi, 2014; Thanki and Baser, 2019). Single individuals have more freedom in making spending and investment decisions while married individuals' investment behaviour are significantly influenced by their marital status, especially when their spouses have different financial personalities (Christiansen et al., 2015). Furthermore, past studies have revealed that married couples exhibit greater wealth and optimistic outlook toward investment than single individuals (Christiansen et al., 2015; Gakhar and Prakash, 2017). Marriage frees up economic resources (Christiansen et al., 2015) and serves as a support system (Gakhar and Prakash, 2017). Hence, married individuals are more willing to take risks in investment. According to Lutfi (2010), families with only two members (i.e., spouses) display the greatest risk-seeking attitude because they have the advantage of a higher household income and shared living arrangements (Grable et al., 2020). Correspondingly, married without dependents is selected as the marital status for the aggressive investor's profile, while single is the chosen marital status for the moderate investor's profile.

7 *Dependants:* Dependants, especially minor children, have an impact on investment behaviour because they diminish the resources available for the family in the long-run (Baker and Ricciardi, 2014). Investment on children can be expensive and parents tend to allocate more wealth, time and effort on their children because of social pressure, the feeling of self-fulfilment and children serving as their parents' markers of success (Gauthier and de Jong, 2021). Some parents even choose to become homemakers after their children are born, which further reduces the household income. When the parents opt to return to work, many of them, particularly women, may face a 'wage penalty' (Budig and England, 2001).

Consequently, the financial burden is higher for families with children. Lutfi (2010) claims that these families tend to display the greatest risk aversion relative to single individuals and married couples with no dependants. In this paper, conservative investor's marital status and dependants are set as married with dependants.

8 *Individual net worth:* Broadly speaking, an individual's cumulative net worth is defined as the balance of assets after deducting liabilities. Stanley and Danko (1996) develop a more comprehensive and detailed formula to derive an individual's net worth, which is widely adopted in the finance and investment industry, as follows:

$$Net\ worth = Age \times \frac{Annual\ income}{10} \tag{A1}$$

Based on equation (A1), a net worth of USD110,038.08 is derived in the construction of investors' profiles in this study.

9 *Investment philosophy and risk tolerance:* Investment philosophy is critical for investors to ensure that their portfolios remain aligned with their objectives, risk tolerance and personalities. According to Damodaran (2012), risk tolerance is correlated with investment philosophy because investors with lower risk tolerance will choose an investment philosophy based on stable returns and less risks. The more risk-averse a person is, the less likely is the person to take on speculative positions in their portfolios because this is perceived as harmful to their personal wealth (Baruah and Parikh, 2018). Accordingly, we adopt the following classifications for risk tolerance and investment philosophy, where a conservative investor has low risk tolerance and requires a stable return and minimum loss, a moderate investor has moderate risk tolerance and requires a higher return and acceptable loss while an aggressive investor has high risk tolerance and requires a maximum return.

10 *Goal of investment:* Goal-based investing is one of the key underlying principles of robo-advisors, where multiple financial goals with varying priorities are collected for personalised financial planning (Kim et al., 2020) and these goals reflect the level of risk aversion of the investors (Shefrin and Statman, 2000). This investment principle places individuals at the centre of the investment decision-making process. Sironi (2016) asserts that the true risk for individual investors is not market volatility but the consistency of personal risk tolerance, ambitions and preference of robo-advisors. For the purpose of generalisation and consistency, this paper indicates 'general investment to increase personal wealth' as the investment goal in the construction of investors' profiles. This is in contrast to Boreiko and Massarotti (2020) who select 'saving for retirement' as the investment goal in their study. We contend that this is not a priority in the case of the sample economies covered in this paper because each economy has its respective statutory retirement schemes.

11 *Investment horizon:* The returns on different types of investment instruments are realised over varying terms or investment horizons. In general, investment portfolios can be classified into three broad investment horizons, i.e., short-, medium- and long-term. According to the World Bank Group (2022), any financial instrument with maturity of more than one year can be defined as long-term. Most of the financial institutions categorise financial instruments with maturities of more than

ten years as long-term instruments. When adopting the robo-advisory services, most of the investors perceive investing within five years as short-term (Fan and Chatterjee, 2020). In spite of this, there is essentially no ideal or average investment horizon (Boreiko and Massarotti, 2020). Theoretically, the longer the investment horizon, the more is the exposure to uncertainties. Nevertheless, the higher returns will compensate for the higher risk (Hickman et al., 2001). For the purpose of generalisability, the medium-term investment period of five to ten years is selected as the investment horizon in the construction of investors' profiles. This is intended to eliminate any extreme dispersion of results due to the investment period.

12 *Monthly investment amount:* There is no one-size-fits-all percentage for investment because it depends on one's income and expense level. According to the majority of past studies and financial planners' advice, the optimal investment portion should fall between the range of 10% and 20% of an individual's income. For example, Greninger et al. (1996) reveal that financial planners typically recommend a saving or investment ratio of 10% from income. Another well-known investment rule is Warren and Tyagi's (2006) 50/30/20 rule which suggests that 20% of income should be allocated for saving and investment. According to Profesia (2022), the median monthly income for the age group 35 to 44 years old in the USA is USD5,724. Nevertheless, the USA is a high-income nation as compared to the seven sample economies in this study, which comprise a mixture of high-income (Singapore, Hong Kong SAR, Japan, South Korea and Taiwan) and medium-income economies (Malaysia and India). Considering that the preceding 50/30/20 methodology (Warren and Tyagi, 2006) is primarily prescribed for the US community but this study consists of a mixture of high- and medium-income economies, a lower percentage of 10% of the average monthly income amounting to USD229.25 is chosen as the monthly investment amount.