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RISK PROFILING QUESTION INVESTIGATION FOR ROBO-ADVISOR

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Abstract. *Purpose* – this study aims to thoroughly investigate by reviewing previous literature on risk assessment queries for robo-advisors, comparing it with three existing robo-advisors and proposing suitable risk assessment questions for robo-advisor.

Research methodology – utilize the deductive content analysis technique to examine the risk assessment issue for financial robo-advisors, which is influenced by previous study.

Findings – there are nine questions share a similar context both in previous literature and among existing robo-advisors, with income being the most commonly used question. Then, there are three questions that are only asked by the existing robo-advisors: emergency funds, home ownership, and the source of transaction. These findings suggest some additional questions to enhance the effectiveness of risk assessment in robo-advisory services for individuals.

Research limitations – only two previous research papers have focused on risk profiling, and three available applications used in this research.

Practical implications – the robo-advisor's developer should take into account various factors such as local culture and economic conditions, financial product knowledge, etc. when crafting diverse risk profiles to provide more precise investment recommendations.

Originality/Value – the study is the first research which explore the risk profiling for financial robo-advisor, which used by existing robo-advisor then compared to other countries in the world.

Keywords: robo-advisor, risk profiling, fintech, literature, content analysis.

JEL Classification: D83, G11, O33.

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1. Introduction

The rise of the internet and artificial intelligence in Indonesia has led to the growth of investment apps that utilize robo-advisors. A crucial aspect of financial robo-advisors is assessing a user's risk profile, which involves posing questions to determine if they are risk-takers, risk-averse individuals, or moderate investors. This information guides the apps in providing tailored investment recommendations. However, determining a user's risk profile accurately poses challenges for robo-advisors, especially algorithm aversion which highlight various factors that influence their adoption in investment. Including confidence levels and personal belief (Alemanni et al., 2020; Filiz et al., 2021), education and financial knowledge (Litterscheidt & Streich, 2020), incentive provision (Niszczota & Kaszás, 2020), robo-advisor identity (Hodge et al., 2021), and thinking about God (Karataş & Cutright, 2023).

To assess the effectiveness of risk profiling in the robo-advisor, we conducted the initial research using Focus Group Discussions (FGD) and an open-questionnaire survey of the 36 students at the school of business management in Indonesia, which have different academic batches. The students consist of sixteen students from 2020 batch who have taken financial and investment-based courses (FIBC), and twenty students from 2021 batch who haven't taken the course (NON FIBC). This preliminary research discover that in the scale 4 (appropriate) and scale 5 (very appropriate), the FIBC group show 50% and NON-FIBC group 79.99% of the students deemed the risk assessment provided by robo-advisors to be suitable for their personal risk profiles. However, despite this positive perception of suitability, 60% of FIBC group and 53.33% of NON-FIBC group students refuse to use the recommendations provided by robo-advisors. This interesting result raises a question: Is the current risk profile of financial robo-advisors in Indonesia appropriate?

Our investigation into prior research on risk profiling for robo-advisors led us to the works of Tertilt and Scholz (2018) and So (2021), who conducted a comparative analysis of risk profiling questions from various countries, such as Australia, Canada, Hong Kong, United States and United Kingdom. Their studies focused on identifying which specific questions influence an individual's risk preference, providing valuable insights into the comprehensive assessment of risk profiles in the developing countries, but there are a lack of comprehensive research examining the range and effectiveness of risk profiling assessment utilized by robo-advisors, particularly in emerging markets like Indonesia. This gap in knowledge is significant as the understanding of user's risk profile is fundamental to fostering trust in robo-advisor platforms. This motivates us to conduct the proper risk assessment, regarding the comprehensiveness and effectiveness of risk profiling questions in the financial robo-advisor platform.

This study aims to examine the risk profiling questions utilized by robo-advisors in Indonesia and compare them with international practices. By referring to previous literature, it aims to identify areas for improvement and provide recommendations for developers of robo-advisory services as well as scholarly literature. This research contributes to broadening the risk profiling literature in the robo-advisor by reflecting on robo-advisor in Indonesia as one of the emerging country. It would give other valuable insights into the application of robo-advisor risk profiling tools, highlighting similarities and differences with global approaches.

This study employs deductive content analysis methods to examine the literature used in current robo-advisors, then suggests alternative questions to promote more comprehensive risk profiling. This research is the first in Indonesia context, which follows previous studies by Tertilt and Scholz (2018) and So (2021).

2. Benchmark literature

A financial robo-advisor is a fintech that combines technological innovation and human interaction to provide personal financial services. It is a digital platform that utilizes algorithms, machine learning techniques, or artificial intelligence to manage thousands of financial products, assets, and user portfolios (Bayón, 2018; Beltramini, 2018; Jung et al., 2019). The design of a financial robo-advisor focuses on digitalization, reducing management costs, and increasing the independence of users (Day et al., 2018; Jung et al., 2018; Shanmuganathan, 2020). It uses a simple investment method to avoid the conflict of interest between investors and human financial advisors (Brenner & Meyll, 2020; Xue et al., 2018).

Unlike traditional advisors, robo-advisors prioritize the independence of their users to assess their self-assessment of risk profiling. It mitigates investor bias, advanced risk profiling analysis techniques such as questionnaire surveys are used (Ahn et al., 2020; Bhatia et al., 2020).

Based on our systematic literature study and bibliometric analysis of financial robo-advisor (Hasanah et al., 2023), we found two studies which focused on risk profiling in robo-advisors using systematic questions i.e., Tertilt and Scholz (2018) and So (2021). Moreover, Jung et al. (2019) use Tertilt and Scholz (2018) study to define the risk assessment and mention that some questions can be used to explore the financial robo-advisor's user personality.

First benchmark study come from Tertilt and Scholz (2018) who explore robo-advisor's risk profiling based in Germany, United Kingdom, and United States. They collaborated with institutions such as private banks, savings banks, cooperative banks, and online risk profiling systems (Fina Metrica). By building an algorithm, they defined risk profiling questions into three categories: general information, risk capacity, and risk tolerance. They analyze the quality of portfolio and measured the effectiveness of robo advisor question. The findings show that the stock ownership in the robo-advisor differs in every country and the stock market households' participants in United Kingdom and United States have more significant participation than households in Germany and other European countries.

Second benchmark study that contributes to the understanding of risk profiling in robo-advisors is So (2021) research. He collected 20 questionnaires from banks and investment

Table 1. Robo-advisor risk profiling question tabulation by Tertilt and Scholz (2018)

General Information	Risk Tolerance
▪ Income	▪ Age
▪ Investment amount	▪ Association with investing
▪ Job description	▪ Association with risk
▪ Other	▪ Choose portfolio risk level
▪ Source of income	▪ Comfort investing in the stock
▪ Spending	▪ Credit-based investments
▪ Time to retirement	▪ Dealing with financial decisions
▪ Type of account	▪ Degree of financial risk taken
▪ Working status	▪ Education
Risk Capacity	▪ Ever invested in the risky asset for the thrill
▪ Dependence on withdrawal of investment amount	▪ Experience of drop/ reaction on drop/ max drop before selling
▪ Income prediction	▪ Family and household status
▪ Investment amount/ savings rate ratio	▪ Financial knowledge
▪ Investment amount/ total capital ratio	▪ Gender
▪ Investment horizon	▪ Investment experience
▪ Liabilities	▪ Investment goal
▪ Savings rate	▪ Investor type/self-assessment risk tolerance
▪ Total capital	Preference returns vs. risk

service providers in various countries, including the Australia, Canada, Hong Kong, United States, and United Kingdom, and gathered 180 questions. Subsequently, he categorized the questions into 16 types and identified five risk factors, denoted as Factors I to V (Table 2). Each factor represents a specific issue that can aid in evaluating risk profiles through a comprehensive assessment of both the capacity and inclination to take risks. It places emphasis on factual data such as investment plans, objectives, timeframes, and customers' financial circumstances, while also considering perception factors like investors' willingness to accept losses and their behaviour during market downturns.

The previous studies by Tertilt and Scholz (2018) and So (2021), have examined risk profiling in various contexts. Although their research centres around risk profiling, they employ different methodologies. However, both studies have constructed questionnaires based on their respective samples, which will serve as a reference point for the present study to understanding of risk profiling questions.

Tertilt and Scholz (2018) study has been criticized for its limited explanation of the question tabulation process, particularly in relation to a question within the general information category. Furthermore, the study's focus on only 60% of the questions that influence risk categorization could potentially reduce the accuracy and effectiveness of determining risk profiles.

On the contrary, a study conducted by So (2021) has been criticized for including samples from providers that do not offer robo-advisor services, particularly those from Hong Kong. Nevertheless, other investment service providers in the non-Hong Kong samples, like Charles

Table 2. Robo-advisor risk profiling question tabulation by Tertilt and Scholz (2018) and So (2021)

No	Question Type	Risk Factor
1	Investment plan/goal and expected return from the investment	Factor I
2	Investment time horizon	
3	Description of investment knowledge and experience	Factor III
4	Description of product knowledge and trading experience	
5	Current asset allocation	
6	Description of the degree of risk willing to take in literal form	Factor II
7	Description of the degree of risk willing to take in quantitative form	
8	Degree of risk tolerance when experiencing investment loss (hypothetical question)	
9	Action would take when experiencing investment loss (Hypothetical question)	Factor IV
10	Percentage of income/net worth for investment	Factor V
12	Financial health check and employment status	
11	Earning capacity of an investor	
13	Age/education level of the investor	
14	Confidence in making own investment decisions	
15	Withdrawing money from investments to fill liquidity needs	
16	Others	

Schwab, Merrill Edge, and Vanguard, do offer robo-advisor services. However, certain question categories are absent So (2021)'s table distribution of questions, for example, the user's income and the currencies available for consideration by investors.

3. Methodology

3.1. Content analysis

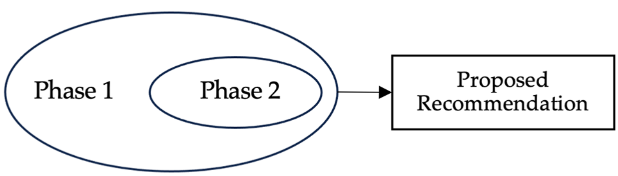
Content analysis is a research technique that utilizes scientific tools to derive reliable and valid conclusions from text within specific contexts, employing specialized procedures. The primary goals of this method are to generate knowledge, gain new insights, present factual representations, and offer practical guidance (Harwood & Garry, 2003; Krippendorff, 2004).

Content analysis facilitates the examination of documents to explore theoretical issues and enhance comprehension of gathered data. It identified concepts or categories can then be used to develop models, conceptual systems, concept maps, or categorical frameworks (Elo & Kyngäs, 2007), and gain insight and knowledge by involving the systematic analysing data (Rastogi et al., 2022).

According to the process analysis, content analysis can be classified into two categories. First, inductive content analysis, referred as data-driven which focuses on moving from specific and concrete observations towards broader theoretical understanding or abstraction (Elo & Kyngäs, 2007; Graneheim et al., 2017; Schreier, 2012). One of our benchmarks is So (2021) study who used content analysis method on risk profiling question identification due to the fragmented of phenomenon and limited knowledge.

Second, deductive content analysis is employed to confirm previous research findings in different contexts and categories, then involves examining theoretical concepts to enhance the comprehension of the data (Elo & Kyngäs, 2007). It is referred to as concept-driven and follows a progression from abstract theories to concrete and specific levels (Graneheim et al., 2017; Krippendorff, 2004; Schreier, 2012).

In this research, we employ the deductive content analysis method to investigate the risk profiling assessment for financial robo-advisors in Indonesia. Our approach is inspired by Tertilt and Scholz (2018) and So (2021) who have conducted benchmark studies on this topic. The research framework presented in Figure 1 guides our content analysis process. The deductive content analysis approach is suitable for our research on risk profiling in financial robo-advisors due to the existing literature and theories available on the topic.



Phase 1: Analysis and Comparison of Previous Study
Phase 2: Analysis and Comparison of Existing Robo-Advisor

Figure 1. Research framework

In the initial phase, the research conducted by Tertilt and Scholz (2018) and So (2021) is compared to gain fresh perspectives on risk profiling questions in financial robo-advisors. In the subsequent phase, we assess and examine the outcomes of Phase 1 in conjunction with existing investment applications that utilize robo-advisors as their service, labelled FRA 1, FRA 2, and FRA 3. In this stage, our objective is to ascertain whether or not these existing robo-advisors adhere to scientific research when it comes to profiling user risk. Additionally, we seek to identify any alternative perspectives not covered by previous studies. In the last stage, the study proposes some appropriate risk profiling questions for financial robo-advisors.

4. Trustworthiness

The challenge in conducting a content analysis is ensuring the trustworthiness of the studies. This method has received criticism from experts in quantitative field, who argue that simple techniques are not suitable for detailed statistical analysis. Additionally, some believe that content analysis alone does not meet qualitative research standards (Morgan, 1993). However, it should be noted that the difficulty level of content analysis can vary depending on the researcher conducting it (Neuendorf, 2017).

Researcher should aim to establish trustworthiness in content analysis by providing a thorough explanation and comprehensive conclusion of their analytical process, data and results (Weber, 1990). Content analysis approach enables readers to gain a clear understanding of how the data was analyzed while being aware of both the strengths and limitations associated with the research findings (United States General Accounting Office, 1996).

To ensure trustworthiness in our research, we conduct the structured matrix and comprehensive analysis to determine the findings and proposed recommendations. This matrix possible to select only aspects that fit into the previous category framework (Elo & Kyngäs, 2007).

5. Findings

5.1. Phase 1: analysis and comparison of previous study

In the first phase, the previous studies by Tertilt and Scholz (2018) and So (2021) are compared to obtain a comprehensive understanding of risk profiling questions in financial robo-advisors. A comparison of the two studies reveals that sixteen out of thirty-five questions from Tertilt and Scholz (2018) intersect with fourteen out of sixteen questions from So (2021) (including the "Others" category) (Appendix shows the intersection highlighted in gray).

Tertilt and Scholz (2018) and So (2021) have different classifications and emphasis on determining risk profiles. Tertilt and Scholz (2018) has more specific categories and greater detail than So (2021), who categorizes more broadly. Table 3 shows some differences between the two studies.

Personal information such as age, education, family and household status, and gender are included in the risk tolerance category in Tertilt and Scholz (2018). However, some personal information impacts risk tolerance, such as age or birth date, which will be changed to some degree (Mandal & Roe, 2007; Jianakoplos & Bernasek, 2006).

Table 3. Comparison between Tertilt and Scholz (2018) and So (2021) study

Tertilt and Scholz (2018)	So (2021)
Have specific general information, such as income, job, source of income, working status, etc.	Do not emphasize general information. The question about income is not the main question.
Emphasis on income as the basis for investment capital.	Emphasis on asset allocation and the earning capacity of the investor. Income and net worth are used to measure the strength of the investor's financial health.
Personal information is not only stated in the general knowledge section but also included in the risk tolerance category.	Do not emphasize personal information.
The risk indicator is divided into two categories: risk capacity and risk tolerance.	The risk indicator is divided into five factors, from Factor I to Factor V.

Tertilt and Scholz (2018) focus on the user's capability in investment, reflected in the types of investments, liabilities, and total capital investors have. Meanwhile, the risk tolerance category emphasizes how well the investor knows the investment activity and the risks that will happen.

In contrast, So (2021) has a different approach to determining risk, dividing it into five factors: Factor I: how an investor sets realistic investment goals, Factor II: an investor's capability to take risks, Factor III: how well the investor knows and understands the investment product, Factor IV: an investor's behavior, and Factor V: an investor's financial health and earning capacity.

The intersection between Tertilt and Scholz (2018) and So (2021) studies highlights certain questions, including investment knowledge (Appendix). However, the asset al.ocation and earning capacity question in So (2021) cannot be compared to the capital question in Tertilt and Scholz (2018) because they have different terms. Asset allocation refers to how an investor allocates their liquid or non-liquid assets, whereas earnings refer to the part of income obtained from employment. Total capital in Tertilt and Scholz (2018) refers to an investor's initial investment.

It is noteworthy that the question about investment knowledge was recognized in both studies. More advanced research can recommend the questions to get comprehensive information about user investment knowledge before using the financial robo-advisor. In fact, financial literacy knowledge in Indonesia is only 38.08%, implying that only 38 out of every 100 Indonesians are financially literate (Financial Services Authority of Indonesia, 2020). Thus, it is crucial to determine financial behavior and avoid financial fraud by assessing investment knowledge before using the financial robo-advisor.

5.2. Phase 1 and phase 2: analysis and comparion of existing robo-advisor

This Section compares the risk profiling questions used by existing robo-advisors in Indonesia, namely Financial Robo-Advisor (FRA) 1, FRA 2, and FRA 3. Each robo-advisor has six questions, ten questions, and fifteen questions, respectively. Every robo-advisor are presented in simple questionnaires in the Indonesian language for ease of understanding by users. Notably, FRA 1 employs an open answer strategy for some questions, which may lead to biased responses due to user estimation although it suitable for gathering specific information from the question. Conversely, FRA 2 and FRA 3 use multiple-choice options that provide more structured responses.

To evaluate existing robo-advisors in Indonesia, we defined nine questions based on the intersection of Tertilt and Scholz (2018) and So (2021) studies. Five questions were drawn from Tertilt and Scholz (2018), one from So (2021), and three were not included in either study (Table 4).

Income is the most asked question in all three robo-advisors, with FRA 1 and FRA 2 inquiring about monthly income, while FRA 3 asks about annual income. Notably, FRA 2 and FRA 3 provide income ranges in Rupiah, while FRA 1 requires users to write their income amount. So (2021) study categorizes the income question as an unclassified or low-occurrence question, with only around 3% being related to background information.

The next question is *age* in FRA 1, which is categorized as risk tolerance based on Tertilt and Scholz (2018) study. Prior research has shown that age decreases risk tolerance (Jianakoplos & Bernasek, 2006; Mandal & Roe, 2007), Tertilt and Scholz (2018) employed robo-advisors and bank samples from the U.S. (80%), U.K. (33%), and Germany (43%), which inquired about the age of their users.

In terms of *investment goals*, only FRA 3 provides detailed questions, including investment objectives and the purpose of utilizing mutual funds' investment results. The multiple-choice investment objectives include appreciation of price, long-term investment, speculation, and income. Moreover, the question of why use the investment results in mutual funds provides options for future education, the next three to five years, or short-term income.

Some case study questions asked to prompt users to take action in facing market situations are categorized as *investor type/self-assessment risk tolerance*. Only FRA 2 employs a case question about choosing a portfolio risk level to determine risk level and decision-making. This question asks about the percentage of worry a user might feel if the market loses. Additionally, FRA 1 and FRA 2 inquire about dealing with financial decisions using a case question such as, *"What will you do if the financial market is very volatile and your investment decreases by 15% in a month?"* The question provides options to sell all, sell separately, hold, or buy again. It can determine risk level by examining the user's reaction when facing uncertainty or loss.

Tertilt and Scholz (2018) have proposed five categories of questions, of which only FRA 3 contains comprehensive questions related to *job descriptions*, including the type of business, job position, and length of work in a year. The type of business question inquiries about multiple options such as a jewelry store, a car marketing agent, and a service, whereas the job position question provides options like owner, commissioner, student, and housewife.

The preference for returns versus risk question is limited to FRA 1 and FRA 2. In FRA 1, users are asked about their opinion on facing profit and loss, and they can choose to maximize profit, avoid loss, or consider both profit and loss equally important. FRA 2 contains two questions on this topic: the first one asks about the user's opinion, with options similar to FRA 1, while the second one inquiry about users' options when faced with two different

Table 4. Comparison of previous studies and existing financial robo-advisor in Indonesia

	No	Assessment Questions	FRA 1	FRA 2	FRA 3
Tertilt and Scholz (2018) and So (2021)		General Information			
	1	Income	x	x	x
	2	Investment Amount		x	
	3	Working Status			x
		Risk Capacity			
	4	Investment Horizon		x	x
		Risk Tolerance			
	5	Age	x		
	6	Education		x	x
	7	Investment Experience		x	x
	8	Investment Goal			xx
	9	Investor Type/Self-Assessment Risk Tolerance	x	xx	
Tertilt and Scholz (2018)	10	Job Description			xxx
	11	Source of Income			x
	12	Spending			x
	13	Family and Household Status	x		x
	14	Preference Return vs. Risk	x	xx	
So (2021)	15	Asset Allocation	x		
Uncategorized	16	Emergency Fund		x	
		Home Ownership			x
		Source of Transaction Funds			x

Note: 'x' shows the number of questions in every existing financial robo-advisor.

investment options: receiving one million Rupiah or having a 50% chance of reaching five million Rupiah. This question is analogous to the experiment question of prospect theory by Daniel Kahneman and Amos Tversky.

So (2021) study indicates that FRA 1 poses only one question related to *asset allocation*, which requires the user to compute the number of assets owned, such as cash, deposits, property, gold, shares, mutual funds, etc.

Interestingly, there are three additional risk profile questions, namely emergency fund, homeownership, and source of transaction funds are absent from the Tertilt and Scholz (2018) and So (2021) studies but present in existing Indonesian robo-advisors. These questions should be included in the general information category as they reflect the user's financial condition.

FRA 2 asks the *emergency fund question* to determine how often users secure their financial lives if they do not have income. Although emergency funds and savings share the same characteristics of holding money, emergency funds are used during household crises

Table 5. Existing questions in Tertilt and Scholz (2018) and So (2021) study but not exist in FRAs

Tertilt and Scholz (2018)	So (2021)
Depending on the amount of investment withdrawn	Withdrawing money from investments to fill liquidity needs
Liabilities	Financial health check and employment status
Dealing with financial decisions	Confidence in making your own investment decisions
Degree of financial risk taken	In literal terms, describe the level of risk you are willing to take
	Description of the level of risk willing to be quantified
Ever invested in the risky asset for the thrill	Description of product knowledge and trading experience
Experience of drop/reaction on drop/max drop before selling	
Financial knowledge	Description of investment knowledge and experience

like long-term illness or joblessness, while savings are accumulated for a specific purpose or to reduce non-essential expenses.

The second question is *homeownership* from FRA 3, which investigates the proportion of the user's expenses, specifically the housing expense portion. The absence of home ownership burdens the user with housing rent expenses, which can also impact their investment portion. This question offers several options, including owned by the husband/wife, official residence, rent, family-owned, and owned by themselves. Furthermore, FRA 3 also asks *the source of transaction funds* to determine the origin of funds for investment, which can be from wages, inheritance, pension funds, etc. Overall, some questions intersect with Tertilt and Scholz (2018) and So (2021), but do not exist in the existing robo-advisors in Indonesia (Table 5).

6. Discussion and recommendations

This paper investigates the diversity of risk profiling questions used by financial robo-advisors in comparison with existing ones. The objective of this study is to examine whether existing risk profiling questions adequately facilitate user risk profiling, as this could have implications for credibility related to robo-advisor usage.

Trust issues related to robo-advisors have been defined in previous studies. For instance, (Filiz et al., 2022) found that 59.69% of their experimental participants refused to use algorithmic decision-making and preferred to choose investments based on their abilities, even though the algorithmic approach performed better, which known as algorithm aversion (Dietvorst et al., 2015). This research aligns with Filiz et al. (2021)'s research about overconfidence in choosing not to use a robo-advisor, despite evidence showing that neither their own judgment nor that of experts is necessarily more successful. Similarly, Alemanni et al. (2020) emphasizes individuals' preference for advice from humans over robot advisors when the opinion aligns with their beliefs. Additionally, Bhatia et al. (2020) discovered that convenience alone, provided by algorithms like robo-advisors, is insufficient to encourage users to follow investment recommendations. This is because users focus to prevent undesirable outcomes from occurring, and focusing more on desired outcomes when using human advisors (Chang & Wang, 2023). Interestingly, thinking about God encourages greater acceptance of AI-based recommendations due to the similarity between AI and God, both being equally mysterious (Karataş & Cutright, 2023).

In addition, the incentive factors also reduce algorithm aversion to robo-advisors. However, there is still a small likelihood of using robo-advisors for investing in certain stocks (Niszczota & Kaszás, 2020). This occurs because algorithms are still considered less effective compared to humans in tasks that require subjective judgment (Castelo et al., 2019), despite efforts to make them more human-like by assigning them names (Hodge et al., 2021). Furthermore, algorithms with slow predictions are considered less accurate, causing users to be reluctant to rely on them. In contrast, slowly generated human predictions are often seen as more reliable (Efendić et al., 2020). On the other hand, the continuous decision-making processes and increasing time pressure in algorithms will reduce algorithmic reluctance (Jung & Seiter, 2021; Rühr et al., 2019).

Considering our findings, this study proposes that a good first engagement, particularly with risk profiling, is crucial for robo-advisors to attract user attention. We provide suggestions for developers of robo-advisors and financial experts specializing in financial robo-advisors in Indonesia. These recommendations aim to ensure that comprehensive user information and investment willingness are obtained by the robo-advisors in Indonesia, considering risk profiles.

First, we propose that robo-advisors ask users about their *level of knowledge regarding financial products* and their *experience with financial investments*. It is crucial to prevent users from misunderstanding financial products, particularly funds allocation instruments. Litterscheidt and Streich (2020) found that the higher levels of knowledge and education tend to make individuals trust robo-advisors more, which ultimately affects investment results. This recommendation aims to help developers classify users into beginners and experts, thereby creating more accurate risk profiles. The ability to invest in financial products comes with expectations of profitability; however, market fluctuations can lead to losses. Therefore, investment literacy is critical, especially for novice investors, to understand how investments work and what types of products to purchase. Displaying legal and government certifications can also be helpful in gaining user trust.

Second, it is beneficial for robo-advisors to inquire about *the individual's level of risk tolerance*. This recommendation beneficial to gain a comprehensive understanding of user's risk level intuition which affect to enable robo-advisors to better comprehend user's risk profile.

Third, the recommendation about concerning the *financial health*. Where the Indonesian people have lack understanding of financial management and literacy in Indonesia (Financial Services Authority of Indonesia, 2020). This recommendation should not only assess income and expenditures but also consider liabilities, savings, and emergency funds. As we found that, although FRA 2 has specifically requested information on emergency funds, other FRAs should also incorporate this inquiry. This strengthens a survey conducted by Lifepal which revealed that 90% of Indonesians do not possess emergency funds (https://www.fimela.com/). Despite variations in definitions, most people still struggle with differentiating between emergency funds and regular savings. Emergency funds are intended for unexpected situations and are saved indefinitely whereas savings are designated for specific goals such as education or marriage expenses. By including this question, robo-advisors can provide investment guidance considering each user's preparedness to cope with market uncertainties.

The risk profile questions are crucial for determining the investment risk profile of users, which can help robo-advisors make suitable investment recommendations based on individual risk preferences and financial circumstances. Once the risk profile has been determined, the appropriate investment product for the user can be automatically selected. However, in practice, existing robo-advisors in Indonesia have not yet incorporated this automatic investment product selection feature, and the choice of investment product still depends on the user. Consequently, when the risk profile changes, only the percentage of the components of the investment product change, such as money market, obligation, or stock. It is hoped that the next generation of robo-advisors in Indonesia will be more sophisticated and incorporate this feature, where the choice of investment product will follow the risk profile of each user.

7. Conclusions

Robo-advisors offer convenient and user-friendly interfaces accessible via mobile phones, as well as personalized financial advice powered by machine learning algorithms. An integral component of robo-advisors is the risk-profile questionnaire, which should be designed to be both user-friendly and accurate in capturing investment preferences for tailored recommendations.

This study compares the risk profiling questions used in previous studies across different countries with those employed in robo-advisors in Indonesia. The results reveal similarities between fifteen common questions from previous studies and nine questions shared by Indonesian robo-advisors. Interestingly, the Indonesian context introduces three additional unique questions that relate to emergency funds, home ownership, and the source of transaction funds. Based on these findings, it is recommended to use comprehensive risk profiling questions that encompass financial product knowledge, investment experience, risk tolerance, and users' financial health for a more accurate assessment of investors' profiles.

8. Implications

The implication of this research is significant academically, practically, and in the regulator context. For academic implication, the unique question from existing robo-advisor in Indonesia can offer fresh insight to contribute to the robo-advisor risk profiling literature, suggesting the necessity of context-specific adaptations.

In the practical implication, this research gives valuable recommendations to improve the effectiveness of risk profiling assessment. The developer can consider the comprehensive question by considering the local culture and economics, which can be defined as financial product knowledge, investment experience, personal risk tolerance, and financial health to construct the various risk profiles and more accurate investment recommendations.

The last is the implication of regulator context. This research suggests the recommendation that can be used to guide the Financial Services Authority of Indonesia to establish the regulation about risk profiling for financial robo-advisors, thus creating more secure and effective financial ecosystem.

9. Limitation and future research

The research is subject to certain limitations, including the fact that only two previous studies on risk profiling were considered, and that only three existing apps in Indonesia claimed to provide robo-advisory services. The study also signals the need for future research on larger and more diverse samples, expanding its implications beyond the Indonesian context and suggesting the potential for global relevance, particularly in comparable emerging markets.

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Author contribution

Eneng Nur Hasanah: Conceptualization, investigation, methodology, writing-original draft, writing-review and editing. Sudarso Kaderi Wiryono and Deddy P. Koesrindartoto: Methodology, validation, supervision, writing-review & editing.

Disclosure statement

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

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APPENDIX

The detailed table of intersection between Tertilt and Scholz (2018), So (2021), and Financial Robo-Advisor in Indonesia

			So (2021)																
			Setting of realistic investment objectives/goals		**Investment knowledge and experience**			**The degree of risk an investor is willing to take**			**Investor behavior**	**Check the strength of an investor's financial health and the income-earning capacity of investors**							
			FACTOR 1		**FACTOR III**			**FACTOR II**			**FACTOR IV**	**FACTOR V**							
			1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**12**	**11**	**13**	**14**	**15**	**16**	**17**
																		Others	
Tertilt and Scholz (2018)			Investment plan/goal and expected return from the investment	Investment time horizon	Description of investment knowledge and experience	Description of product knowledge and trading experience	Current asset al.ocation	Description of the degree of risk willing to take in literal form	Description of the degree of risk willing to take in quantitative form	Degree of risk tolerance when experiencing investment loss (hypothetical question)	Action would take when experiencing investment loss (hypothetical question)	Percentage of income/net worth for investment	Financial health check and employment status	Earning capacity of an investor	Age/ education level of the investor	Confidence in making own investment decisions	Withdrawing money from investments to fill liquidity needs	What is your total monthly income	Please select up to six currencies you may consider for investments in this account
1	**GENERAL INFORMATION**	Income																FRA1 FRA2 FRA3	
2		Investment amount										FRA2							
3		Job description																	
4		Other																	
5		Source of income																	
6		Spending																	
7		Time to retirement																	
8		Type of account																	
9		Working status											FRA3						

Continue of Appendix

Tertilt and Scholz (2018)			So (2021)																
			Setting of realistic investment objectives/goals		Investment knowledge and experience			The degree of risk an investor is willing to take			Investor behavior	Check the strength of an investor's financial health and the income-earning capacity of investors							
			FACTOR 1		FACTOR III			FACTOR II			FACTOR IV	FACTOR V							
			1	2	3	4	5	6	7	8	9	10	12	11	13	14	15	16	17
																		Others	
			Investment plan/goal and expected return from the investment	Investment time horizon	Description of investment knowledge and experience	Description of product knowledge and trading experience	Current asset al.ocation	Description of the degree of risk willing to take in literal form	Description of the degree of risk willing to take in quantitative form	Degree of risk tolerance when experiencing investment loss (hypothetical question)	Action would take when experiencing investment loss (hypothetical question)	Percentage of income/net worth for investment	Financial health check and employment status	Earning capacity of an investor	Age/ education level of the investor	Confidence in making own investment decisions	Withdrawing money from investments to fill liquidity needs	What is your total monthly income	Please select up to six currencies you may consider for investments in this account
10	RISK CAPACITY	Dependence on withdrawal of investment amount																	
11		Income prediction																	
12		Investment amount/ savings rate ratio																	
13		Investment amount/ total capital ratio																	
14		Investment horizon		FRA2 FRA3															
15		Liabilities																	
16		Savings rate																	
17		Total capital																	

Continue of Appendix

Tertilt and Scholz (2018)			So (2021)																
			Setting of realistic investment objectives/goals		**Investment knowledge and experience**			**The degree of risk an investor is willing to take**			**Investor behavior**	**Check the strength of an investor's financial health and the income-earning capacity of investors**							
			FACTOR 1		**FACTOR III**			**FACTOR II**			**FACTOR IV**	**FACTOR V**							
			1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**12**	**11**	**13**	**14**	**15**	**16**	**17**
																		Others	
			Investment plan/goal and expected return from the investment	Investment time horizon	Description of investment knowledge and experience	Description of product knowledge and trading experience	Current asset al.ocation	Description of the degree of risk willing to take in literal form	Description of the degree of risk willing to take in quantitative form	Degree of risk tolerance when experiencing investment loss (hypothetical question)	Action would take when experiencing investment loss (hypothetical question)	Percentage of income/net worth for investment	Financial health check and employment status	Earning capacity of an investor	Age/ education level of the investor	Confidence in making own investment decisions	Withdrawing money from investments to fill liquidity needs	What is your total monthly income	Please select up to six currencies you may consider for investments in this account
18	**RISK TOLERANCE**	Age													FRA1				
19		Association with investing																	
20		Association with risk																	
21		Choose portfolio risk level																	
22		Comfort investing in the stock																	
23		Credit based investments																	
24		Dealing with financial decisions																	
25		Degree of financial risk taken																	
26		Education													FRA2 FRA3				
27		Ever invested in the risky asset for the thrill																	

End of Appendix

Tertilt and Scholz (2018)			So (2021)																
			Setting of realistic investment objectives/goals		**Investment knowledge and experience**			**The degree of risk an investor is willing to take**			**Investor behavior**	**Check the strength of an investor's financial health and the income-earning capacity of investors**							
			FACTOR 1		**FACTOR III**			**FACTOR II**			**FACTOR IV**	**FACTOR V**							
			1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**12**	**11**	**13**	**14**	**15**	**16**	**17**
																		Others	
			Investment plan/goal and expected return from the investment	Investment time horizon	Description of investment knowledge and experience	Description of product knowledge and trading experience	Current asset al.ocation	Description of the degree of risk willing to take in literal form	Description of the degree of risk willing to take in quantitative form	Degree of risk tolerance when experiencing investment loss (hypothetical question)	Action would take when experiencing investment loss (hypothetical question)	Percentage of income/net worth for investment	Financial health check and employment status	Earning capacity of an investor	Age/ education level of the investor	Confidence in making own investment decisions	Withdrawing money from investments to fill liquidity needs	What is your total monthly income	Please select up to six currencies you may consider for investments in this account
28	**RISK TOLERANCE**	Experience of drop/ reaction on drop/ max drop before selling																	
29		Family and household status																	
30		Financial knowledge																	
31		Gender																	
32		Investment experience			FRA2 FRA3														
33		Investment goal	FRA3																
34		Investor type/ self-assessment risk tolerance								FRA2	FRA1 FRA2								
35		Preference returns vs. risk																	