Enhancing students' financial literacy through generative artificial intelligence measuring financial education experiences:

Exploring the importance of personalization of generative AI to enhance financial literacy and the mediating role of credibility on the customer experience.

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Abstract

This research investigates how generative Artificial Intelligence (AI) can be utilized to enhance financial literacy amongst students. This demographic is identified to have lower financial literacy compared to other demographics. The past decade has seen substantial developments with AI and how it can successfully replace human-agents. This thesis therefore aims to examine how students experience generative AI-content to enhance their financial literacy. The role of personalization (vs. non-personalization) on students' perceived credibility, customer experience and behavioral outcomes is examined. Generative AI is very easy to modify and can be easily adapted to fit individual students' needs. Personalization is therefore hypothesized as a promising factor in the setting of this thesis.

The findings were analyzed using Partial Least Square – Structural Equation Modelling (PLS-SEM). The results revealed that personalization of generative AI-content has a significant influence on the behavioral outcomes of the students. Furthermore, this research hypothesized the importance of perceived credibility on the customer experience and behavioral outcomes. However, the results showed no significant effects of perceived credibility on the constructs measured. These insignificant outcomes might be explained by the fact that in information rich environments, people often don't have the cognitive capacity and time to systematically evaluate the credibility of AI. Different control variables have been researched in this thesis, identifying significant differences between demographics. These insights underline the importance of tailoring generative AI-content to fit a person's needs to enhance engagement and its effectiveness.
Overall, this research contributes to give a deeper understanding students' perceptions of generative AI and how this novel technology can be leveraged to enhance financial literacy.

Keywords: Financial literacy, personalization, eye-tracking, perceived credibility, customer experience

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1. Introduction

Improving financial literacy amongst the population is a crucial concern amongst governments and institutions (Knoll & Houts, 2012). Especially amongst college students a lot of gains can be made with improving their financial literacy as students often worry about their finances (Montalto et al. 2018). Research by the European Union/OECD (2020), shows that about 50% of the EU adult population does have an inadequate understanding of basic financial concepts. The European Commission has concluded that there is a need, especially for younger people, to improve financial education. Financial literacy is fundamental to people's financial well-being and protects individuals from taking unnecessary risks, fraud, and helps with the protection of the consumer (European Commission, 2023). This shows the urgent need in improving financial literacy, especially for students. Young people, including students, score significantly worse on financial literacy and financial attitude scores (European Commission, 2023). Addressing this aspect can lead to young people making better financial decisions leading to more financial well-being which will ultimately benefit the society.

Research has attributed different definitions to financial literacy. Most researchers define financial literacy as the knowledge of fundamental financial concepts. These concepts include topics like interest compounding, inflation and percentage calculation (Bajaj & Kaur, 2022). Moreover, how well a person can use financial related information is an important concept of financial literacy (Huston, 2010).

Managers are experimenting with artificial intelligence-driven tools to replace human agents (Crolic et al. 2021). The past decade has seen substantial developments with artificial intelligence (AI) and their applications (Babina et al., 2024). One way to try and improve financial literacy is by using generative AI. The use of AI tools to support learning and enhance knowledge has seen major growth (AI And Education: Guidance For Policy-makers, 2021). Research on the educational benefits of AI shows promising results in using AI in an educational setting. Leiker et al. (2023) states that using generative AI in educational settings has proven to be a viable substitute for learning videos produced via traditional methods. These promising results shows us that generative AI might be used to improve financial literacy.

One benefit of generative AI, in contradiction to regular learning methods, is the adaptability of generative AI. Generative AI is very easy to modify, in an educational setting, a prompt can be easily changed to fit a person's individual needs (Leiker et al. 2023). Therefore, personalization of generative AI content could be a promising factor in the setting of this thesis.

Montgomery and Smith (2008) state that personalization can be defined as ''the adaptation of products and services by the producer for the consumer using information that has been inferred from the consumers' behavior or transactions''. In the context of this thesis, using personalized generative AI to improve financial literacy, there will be a focus on delivering content tailored to the interests of individual students. Personalization of content has an significant impact on decision outcomes. According to Tam & Ho (2006), content that is relevant to an individual has significant effects on decision outcomes, where individuals are more likely to accept offers when these are self-referent.

Generative AI has the capability to learn from experience, and thus, automatically provide educational content, tailored to individual students. Tailored content can make sure that students don't get information overload but learn topics that are applicable to their personal situation. According to the study of Jarodzka et al. 2017, personalizing content can lower the cognitive load (extraneous load) of a student. Excessive cognitive load can impair the students' ability to absorb information that is provided, potentially hindering financial literacy improvements (Strycharz et al. 2019). It is therefore hypothesized that tailored generative AI content will optimize the learning gains of a student, ultimately improving their financial literacy.

To improve financial literacy, students will have to interact with the generative AI and listen to the information they receive. The credibility of the source is an important aspect whether someone will act on provided information, especially in a context where computers give advice (Fogg, 2003). Mainly because the influence of a communicator comes from source characteristics, such as credibility (Kruglanski et al. 2005). Furthermore, a study by Wilson & Sherrell (1993) shows that a message source that is perceived as having high-credibility is more likely to persuade an individual to adopt a behavior, compared to a low-credibility message source. This indicates that credibility has a significant impact on behavioral outcomes.

Credibility is a multi-dimensional construct consisting of expertise and trustworthiness (Hovland et al. 1953). Only when a source is perceived as high on both these dimensions, the source is deemed as credible (Yoo & Gretzel, 2008). Therefore, this thesis will investigate the effects of perceived credibility on the customer experience. The customer experience has a critical role in optimizing performance in the costumer journey (Lemon & Verhoef, 2016).

In order to assess the effectiveness of generative AI and the effects on the customer experience, this research will examine behavioral outcomes. In the context of this study, behavioral outcomes are crucial to evaluate the impact of generative AI on the customer experience. Behavioral outcomes can be seen as the expanded effort of the participant, like making a decision to act. (Morales et al. 2017). In context of this thesis, participants have the decision to collect a flyer after the interaction with the generative AI, this will serve as a representation of their interest and engagement with the technology.

The aim of this research is to provide insights in how generative AI can improve financial literacy amongst students. Therefore, this research explores the impact of personalized generative AI on the customer experience, investigating the influence of perceived source credibility and participants' decision to act. Exploring these relationships will help researchers to understand how to leverage AI technology to ultimately improve financial literacy amongst individuals. The findings will provide knowledge on the effectiveness of personalization of generative AI on behavioral outcomes and the role of perceived source credibility. Ultimately, this research aims to benefit the community by increasing financial literacy amongst the population which will lead to more economic well-being.

2. Literature review

2.1 Generative artificial intelligence

Generative artificial intelligence (AI) is a form of AI that can create a wide range of different content, such as text, audio, images, and videos (Lv, 2023). Different than regular AI models, generative AI models are typically trained using uncontrolled learning. This means that the model learns to identify data characteristics without specific instructions (Abrokwah-Larbi, 2023). Furthermore, generative AI has the capacity to integrate various customer datasets, making it especially useful technology for companies because it can summarize customer-related trends and make compelling customer profiles for personalization (Abrokwah-Larbi, 2023). Artificial intelligence technologies, such as deep learning, internet of things and smart data, are important instruments that enables generative AI to apply personalization to customers (Striuk & Kondratenko, 2021). By leveraging generative AI technology, we can offer tailored financial education to students, enhancing their financial literacy.

2.2 Financial literacy

In the existing literature there are different definitions attributed to financial literacy. Most of the research defines financial literacy as the knowledge of fundamental financial concepts. These concepts include topics like interest compounding, inflation, and percentage calculation (Bajaj & Kaur, 2022). The research of Bajaj & Kaur (2022) states that financial knowledge, financial attitude, and financial behavior should be seen as components of overall financial literacy. Servon and Kaestner (2008) stated that financial literacy refers to a person's ability to understand and use financial concepts. However, financial literacy does not guarantee predictable behavior or improved financial well-being because of other factors (Huston, 2010).

Thorough research on the financial literacy topic has been conducted by different scholars. According to the research of Huston (2010), where there have been seventy-one studies examined on the topic, the terms financial literacy, financial knowledge and financial education are used interchangeably. Huston (2010) conclude that financial literacy could be conceptualized having two dimensions. These dimensions are personal finance knowledge and personal finance application.

Scholars agree on the fact that financial literacy is more than financial knowledge, it also includes attitude, behavior, and skills (Hisgilov & Silber, 2019).

The G20 leaders have adopted a definition of that suggests that financial literacy is ''a combination of awareness, knowledge, skill, attitude, and behavior necessary to make appropriate financial decisions and ultimately achieve individual well-being'' (Hisgilov & Silber, 2019). The definition used by the G20 leaders, discussed in the paper of Hisgilov & Silber (2019) is a good fit in the context of this thesis. This definition fits the scope of this thesis topic, where financial literacy and behavioral outcomes are examined.

Leiker et al. (2023) explored the effectiveness of generative AI videos in an educational setting. The promising results of the study suggests that generative AI content is a great substitute for traditional educational content. One of the major benefits of generative AI is the ability of personalizing educational content. Therefore, we can hypothesize that incorporating personalized generative AI to enhance financial literacy will have a positive influence on the participants' decision to act, ultimately resulting in higher financial literacy amongst students.

2.3 Personalization

There are different definitions of personalization in the literature. According to Montgomery and Smith (2008) personalization can be defined as ''the adaptation of products and services by the producer for the consumer using information that has been inferred from the consumers' behavior or transactions.'' In the marketing context personalization is generally referred to as delivering the right content, to the right person, at the right time (Aguirre et al., 2015). However, in this marketing context, personalization is often studied alongside customization.

According to Versanen (2007) there is no consensus on the relationship between personalization and customization. Conforming to Imhoff et al (2001) customization is considered as a form of personalization. Other scholars, like Kumar et al. (2019) states that customization takes place when a customer proactively defines one or more components of the marketing mix themselves. When the firm decides what marketing mix is the best fit for the customer, they talk about personalization. Furthermore, Aguirre et al (2015) states that personalization is in contrast with customization, where the customer chooses the elements of the marketing mix themselves. Strycharz et al (2019) states that customization takes place when the relevant content is not automated but decided by the consumer, thus the personalization is self-driven. These findings suggest that the relationship between personalization and customization is nuanced and can vary depending on the context.

In the context of this thesis, using personalized generative AI to improve financial literacy, the focus will be on tailoring content to individual students.

This aligns with the definitions of Kumar et al. (2019) and Aguirre et al. (2015) where they state that personalization occurs as a customer-oriented marketing strategy that tries to deliver the right content, to the right consumer, at the right time. This strategy only requires little effort by the student. Personalization can significantly influence the behavior of students, making them more engaged and influenced by the content, which will ultimately benefit in enhancing their financial literacy.

According to Tam & Ho (2006), content that is relevant to an individual has significant effects on decision outcomes and behavior, where individuals are more likely to accept offers when these are self-relevant. Their research also indicates that relevant content is more accurately recalled by individuals and that offers are accepted to a larger extent when they are self-relevant. Therefore, when educational generative AI content is aligned with the students' preferences, personalization can enhance their experience and lead to higher financial literacy. Furthermore, individuals can benefit from personalization as it entails better preference matching, better products, better communication, and a better experience (Vesanen, 2007). Using personalization techniques, we can offer educational content that better aligns with the students' interests which will significantly change their behavior in comparison to non-personalized content. Based on this knowledge, the following hypothesizes are made:

H1a: Personalization of generative AI will have a positive effect on the participants' decision to act.

H1b: '*Personalization of generative AI will have a positive effect on the participants' learning motivation'*

2.3.1 Personalization with AI

AI technology can overcome personalization limitations of traditional physical salespersons. By integrating multiple sources of information, AI can generate data-driven and personalized offers for customers (Canhoto et al., 2023). For example, generative AI leverages deep learning to enable firms to offer targeted marketing experiences and content to their customers at a large scale. The deep learning application of generative AI is trained to analyze smart data, such as customer behavior data, transaction data and customer information, to predict the needs of a customer and provide personalized marketing experiences (Abrokwah-Larbi, 2023).

Kumar et al. (2019) states that the high degree of personalization is a significant factor in the popularity of AI. When technology works on a personal level, and marketers can tap in such a connection, there is a massive potential for customer value. However, the success of personalization is limited by the volume and quality of consumer information available. The capacity of a firm to develop insights, and its ability to implement these insights is also a limiting factor (Kumar et al. 2019).

2.3.2 Personalization in learning

When learning about a subject, there often is an abundance of information which can overwhelm the student. A viable option to deal with information overload is to adapt the environment to the learner, this is called instructional design (Jarodzka et al. 2017). With instructional design we try to make use of the cognitive information processing system in an optimal way to make efficient learning gains (Jarodzka et al. 2017). In an educational environment, personalization offers multiple advantages, especially in effective learning experiences.
This research focuses on leveraging generative AI to enhance financial literacy, which includes educating the participant to ultimately enhance their financial literacy.

According to Leiker et al. (2023), the usage of generative AI in educational settings has proven to be a viable substitute for learning videos, which are considered as traditional methods. Especially in terms of costs and time efficiency the generative AI has a high advantage in comparison.

Moreover, Leiker et al. (2023) emphasizes the fact that the adaptability in generative AI content is substantially more efficient in comparison to traditional methods. The methods used for generative AI allows for simple editing of the used script to create new content. This advantage in comparison to traditional methods allows for high-quality educational content that is up to date (Leiker et al. 2023).

The results from the study of Leiker et al. 2023 indicates that there is little to no difference in learner perceptions between the generative AI content and traditional produced video content. In both the traditional video and the generative AI content, Leiker et al. 2023 concluded that there were significant improvements from pre- to post-learning, with no significant differences between the two methods. Furthermore, According to Jackson & Farzaneh (2012), cognitive load effects decision making and well-being. This might affect the participants' behavioral outcomes, like their decision to take a flyer.

Essentially, excessive cognitive load will impair the student's ability to learn from the information provided by the generative AI, thus hindering improvement in financial literacy.

As stated before, one of the advantages of personalization is that it can be used to address information overload (Strycharz et al. 2019). Excessive cognitive load can have a negative impact on the participants customer experience and their ability to absorb the provided information, potentially hindering improvements in financial literacy. Based on this premise, this thesis hypothesizes the following effect of personalization:

H2: Personalization of generative AI will have a negative effect on the cognitive load of the participants.

2.4 Customer experience

Customer experience has gained a lot of interest amongst academics and practitioners. This concept is defined in diverse ways by different scholars (Chahal & Dutta, 2014). Customer Experience is discussed in many different disciplines. Brands have been focusing more on the customer experience instead of the functional benefits of their service to create a competitive advantage (Sirapracha & Tocquer, 2012). There is an increased importance of customer experience as it gives great benefits for firms in today's society (Lemon & Verhoef, 2016). The increased focus of firms on customer experience is due to the fact that customers interact with firms on multiple touchpoints, this creates a complex customer journey (Lemon & Verhoef, 2016).

Although there are different views on the definition of customer experience and how to measure it, the definitions mainly focus on the service process and its interactions that have an influence on the customer's feelings. It can be considered as an outcome of the interaction between the customer and the service provided (Sirapacha & Tocquer, 2012).

Moreover, there is an agreement that the customer experience is a multidimensional construct, and it involves the cognitive, sensorial, emotional, and social components (Lemon & Verhoef, 2016).

2.4.1 Cognitive dimension of customer experience

The customer experience of a person depends on a customers' cognitive elements (Roy et al., 2020). The cognitive dimension of customer experience assesses different factors, in a retail setting these factors include satisfaction, intrigue, and if the service/product appeals to the customer (Roy et al., 2020).

These cognitive elements can be measured through a products' utilitarian value. In this thesis the cognitive dimension is seen as a psychological variable, this includes cognitive experience measures like the cognitive effort of the participant.

Research by Roy et al. (2020) indicates that personalizing customer journeys can be both an opportunity or a threat to the cognitive customer experience. This depends on the context of the personalization. One of these threats, in a retail setting, is cognitive overload and this can negatively affect the customer experience (Roy et al. 2020).

When enhancing financial literacy, the cognitive customer experience is a key factor. The cognitive load theory can account for different outcomes in enhancing financial literacy. The cognitive load theory is centered around the way in which cognitive resources are used and focused during learning (Schrader & Bastiaens, 2012). Enhancing financial literacy, therefore, depends on the cognitive capacity of the student. Moreover, Schrader & Bastiaens (2012) state that the cognitive load theory is based on the difference between long-term (unlimited) and working memory (limited). This limitation of working memory can be seen as ''the bottleneck of learning'' (Schrader & Bastiaens, 2012). Thus, a lower cognitive load is important in order to successfully educate students to ultimately improve their financial literacy.

Eye-tracking can provide interesting insights regarding the cognitive customer experience of the student. Research from Hermes and Riedl (2021) indicates that the cognitive dimension of customer experience can have a positive influence on behavioral outcomes, such as level of satisfaction, purchase intentions and loyalty. Their research has been done in a retail setting but could be applicable to this experiment as well. Furthermore, Hermes and Riedl (2021) noted that there is still a research gap on neuromarketing measures, like eye tracking, on customer experience outcomes. Based on these insights, the following hypothesis is derived:

H3: The cognitive experience of the student has an influence on a participants' decision to act. Where a low cognitive load will lead to more decisions to act, in comparison to a higher cognitive load.

2.5 Behavioral outcome: the decision to act

This thesis focuses on behavioral outcomes of the participant. In this experiment the behavioral outcome will be measured as ‘the decision to act’. When an experiment focuses on behavior researchers often use choice as their dependent variable. This can be a decision to purchase, the decision to search, or the decision to get rid of something (Morales et al, 2017). In this thesis the behavioral outcome will be defined as the decision to act, where the decision to act refers to a participants’ choice to take home a flyer with more information regarding financial topics. This choice will be presented to the participants at the end of the experiment.

Understanding the factors that influence the decision to act amongst students is crucial when we examine how we can leverage AI to improve their financial literacy. One key factor that can influence their decision is the perceived source credibility. Credibility is hypothesized to have a direct effect on the behavioral outcomes in this research, it plays an important role in mediating the relationship between personalization and customer experience. Perceived source credibility can offer deeper insights into how generative AI can be used to enhance financial literacy.

2.6 Perceived source credibility

Research by Hofland and Weiss (1951) has shown that messages ascribed to high credibility sources tend to be accepted to a greater extent than messages ascribed to low credibility sources. Moreover, the learning theory paradigm of Hovland et al. 1953 suggests that the communicators’ influence on the receiver comes from source characteristics such as credibility (Kruglanski et al., 2005). According to Fogg (2003), when getting advice, the credibility of the source and the information provided are important. Fogg (2003) states that source credibility especially matters when computers give advice or provide instructions to their users. This indicates that source credibility is an important factor when generative AI provides advice, knowledge or instructions to the participants of this experiment. Research by Wilson & Sherrell (1993) indicates that a message source that is perceived as having high-credibility is more likely to persuade an individual to adopt a behavior compared to a low-credibility message source.

Yoo and Gretzel (2008) state that source credibility is defined as ‘’judgements made by a message receiver concerning the believability of a communicator.’’ They argue that source credibility has a positive correlation with the message recipients’ attitudes and behavioral intentions as well as behaviors.

Credibility is not absolute, it rather depends on the social context in which information seeking is pursued and credibility judgements are made (Little & Green, 2021).

This thesis tries to understand how to leverage generative AI to enhance students' financial literacy. It is therefore important to take the credibility of the source into account. The evaluation of a source is determined by how credible that source is. This credibility can be gained through perceived expertise and trustworthiness (Smith et al., 2012).

2.6.1 Source credibility dimensions

Credibility is a multi-dimensional construct. Literature on credibility has proposed various dimensions, these include dynamism, attractiveness, authoritativeness, and character. However, these dimensions have been a subject to debate. There is, however, a general consensus on the importance of the dimensions trustworthiness and expertise.

The research from Yoo and Gretzel (2008) insists that a source is only perceived as credible when identified high on both trustworthiness and expertise. Furthermore, Yoo and Gretzel (2008) claims that a source has to have a positive score on both of these dimensions in order to be perceived as credible. The findings from Yoo and Gretzel (2008) are confirmed by the early research of Hovland et al. (1953) and Kelman (1961) where they state that the dimensions expertise and trustworthiness are the most important regarding source credibility. Overall, the research done on credibility aligns in the fact that credibility's primary dimensions are expertise and trustworthiness (Hovland et al., 1953; Wilson, 1983; Yoo & Gretzel, 2008; Serman & Sims, 2022).

This thesis conceptualizes source credibility as two-dimensional construct, consisting of expertise and trustworthiness, perceived by the message recipients. According to the credibility theory, both dimensions trustworthiness and expertise will influence the credibility of AI generative content.

Expertise:

The first dimension of source credibility is expertise. Expertise can be defined as source quality, including the knowledge or skills to make certain claims about a certain subject (Ohanian, 1990).
The dimension expertise entails the ability of a communicator in a specific domain, perceived by the recipient (Hovland et al., 1953).

Trustworthiness:

Hovland & Weiss, 1952 state that trust is only a perception in people's minds. Trust is not specified as an empirical reality, but it can be created, managed and cultivated in the mind. Trustworthiness is therefore determined by a consumer's trust in the communicator's intention to make valid arguments (Hovland et al. 1953). Furthermore, a study by Bleier et al. (2018) indicated that trustworthiness influenced the relationship between the cognitive experience and purchase intention. Based on this premise, the mediating factor of perceived credibility in the relationship between personalization and customer experience is hypothesized. Specifically, personalization is expected to enhance perceived credibility, which will positively affect the cognitive load and behavioral outcomes.

De Keyzer et al. (2022) suggests that personalization leads to more visual attention, more careful processing, and higher behavioral intention because it benefits the perception of credibility. Furthermore, the study by Chaiken and Maheswaran (1994) has given insights in the relationship between perceived source credibility and influencing peoples' responses to information given. When people process information, the assessment of source credibility is a critical factor in ultimately shaping their behavior.

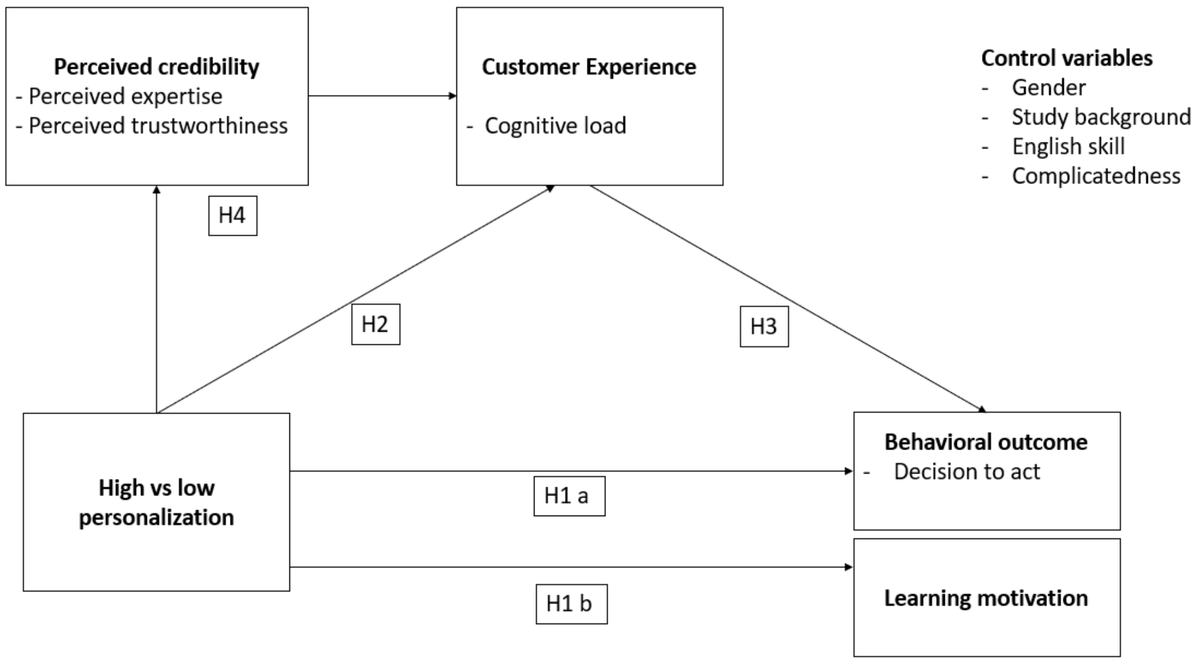
Based on these insights, the following hypothesis is formulated:

H4: The relationship between personalization and cognitive load is mediated by perceived source credibility, such that personalization influences perceived source credibility, which in turn affects cognitive load.

Understanding how both trustworthiness and expertise can shape the participants' perceived source credibility is important when leveraging generative AI to enhance financial literacy. When the generative AI is perceived as both trustworthy and expert this can help to effectively engage participants with the content, thus help improving their financial literacy. Trustworthiness explains the sincere intentions of the generative AI in the eyes of the receiver and expertise gives the generative AI its authority. When prioritizing both these dimensions this will positively affect message recipients' attitudes and behavioral intentions as well as behavioral outcomes (Yoo & Gretzel, 2008).

2.7 Conceptual model

The following conceptual model is derived from the hypotheses in the literature review:



3. Method

The conceptual model and the hypothesis of this thesis are tested with a lab experiment in a generative AI context. The choice for an experiment is made because it allows us to observe the participant's behavior in a controlled environment. This ensures that any observed effects can be attributed to the manipulation in the experiment.

3.1 Research design

The experiment of this thesis is using the Wizard of Oz approach (WOZ). The WOZ approach allows us to observe the student while they are engaging with the generative AI in the experiment. This technique makes the user believe that they are engaging with a fully functional system, however, the missing functionality is supplemented by a 'hidden wizard' (Salber & Coutaz, 1993). This method allows for a realistic interaction between the student and the generative AI, without needing a fully functional system.

In other words, in this experiment the participant thinks they are interacting with the technology, instead they are interacting with one of the researchers. The participant will not be informed about the goal of the experiment to make sure that they are unbiased.

In this experiment, there will be two scenarios for manipulation: Personalized and non-personalized content. This is realized by having one AI-avatar equipped with a generic financial literacy script and a personalized financial literacy script. Each participant will be randomly assigned to one of these two conditions. The scripts are based on a prompt designed by Mollick and Mollick (2023) and adjusted to fit the context of this experiment.
A full script of the prompts can be found in Appendix 1. The script of the AI-avatar can be found in Appendix 2. The subjects for each script were determined based on a survey we conducted for 43 students. In this survey we've asked students several questions regarding financial subjects to determine what topics to include in the experiment (Appendix 3).The personalized scripts were based on the three most popular topics of financial literacy: loans, investing and budgeting. The non-personalized scripts were based on the topics that were the least interesting according to the students. The scripts were uploaded to an AI text-to-video generator named Vidnoz, they were shown in the experiment using video playlists made with VLC Media Player.

3.2 Pre-test of manipulation

Prior to the actual experiment, a pre-test has been conducted. This pre-test was conducted to determine whether the manipulation (personalized vs non-personalized) were significantly different from each other. However, this manipulation failed to show a significant difference amongst the two conditions ($p = .351$). Research shows that perceived personalization drives the effectiveness of personalized messages, not actual personalization (Li, 2016). The participants did not perceive differences between the personalized and non-personalized content. The non-personalized group still perceived the content provided as personalized which lead to insignificant differences between the two groups. To overcome this obstacle we've altered the non-personalized script based on the least relevant financial literacy topic from the survey, retirements. This resulted in significant differences between the two groups ($p < .001$) (Appendix 4).

3.3 Procedure of the experiment

Participants are invited to participate in an AI-experiment. Before the experiment, the participant is informed that they are going to interact with an AI-avatar while wearing an eye-tracking device. Upon arrival, the participant is asked to sign a consent form (Appendix 5).

After signing, the participant receives a number between 1 and 200, selected by a random number generator. The numbers 1 – 100 will be interacting with the personalized content. The numbers 101-200 will receive non-personalized content. After receiving a number, the participant will enter the experiment room and gets instructed by one of the researchers. The participant is instructed to silence their phones and will receive further information about the interaction. The participants are informed that they will interact with an AI avatar and should respond verbally to the AI's questions in English. Researchers emphasize that participants should behave naturally and are allowed to be critical.

If the AI is not responding they are instructed to repeat their answer. Next, the participant can put on the eye-tracking device and get comfortable. After that the eye-tracker will be calibrated using a laptop and the participant is instructed to not touch the device. After calibration of the device, the confidence will be checked, this value should be close to 1.00 but at least > 0.60 (Pupil Labs, n.d.).

If the confidence value does not meet the criteria the device will be calibrated again to make sure that the collected data is useful. Next, the researcher starts the recording and leaves the room. The AI avatar will then start playing the script and is controlled by another researcher (the wizard) in a different room. The researchers in the other room are collecting the data using a Qualtrics survey. Upon completion of the experiment, the researcher enters the room to ask the participant about their experience, and to address any comments or questions. If there are no further inquiries, the debriefer thanks the participant for their participation. This is the end of the experiment. The researcher then renames the data file to match with the participant's assigned number and notes if the participant took a flyer.

3.2 Measurement

As mentioned before, participants are either assigned to personalized or non-personalized generative AI content. The behavioral outcomes of these two groups will be measured. From a broad perspective, anything that a participant does in an experiment can be considered behavior (Morales et al., 2017).

One way to accurately measure behavior of the participants is to include consequence. For example, this means that a researcher does not ask for the likelihood of a participant to donate, but actually measure if the participant donates. Behavioral outcomes can therefore be seen as expanded efforts of the participant, like making the decision to act (Morales et al. 2017).

In context of this research, behavior will be measured by giving participants the opportunity to collect a flyer for more information about a financial literacy topic. They can choose between loans, investing and budgeting. This opportunity will be given after the interaction, so the participant is not distracted by the questions during the experiment. If the flyer is taken, this serves as behavioral evidence (Morales et al. 2017). In the context of this thesis, behavioral outcomes are measured as 'the decision to act'. If the participant takes the flyer, this is characterized as the decision to act.

3.2.2 Cognitive load measurement

Eye-tracking technology will be used to measure the customer experience of the participant. This research focuses on the cognitive dimension of customer experience. Using eye-tracking technology, effects on the cognitive load of the student will be examined. Hereby cognitive load refers to the amount of mental effort being used in the working memory of the participant.

Eye tracking can offer valuable information based on monitoring eye movements (Zagermann et al., 2016). This technology is often used to accurately measure behavior during an experiment. Eye-tracking can measure the cognitive load in multiple ways, for example by measuring the fixations, saccades, and pupil dilations (Zagermann et al. 2016). In this research, the customer experience is measured by looking at the average pupil dilations of the participants.

Pupil dilation is an eye measurement where the diameter of the pupil is examined. Research has shown that pupils dilate when an increase of cognitive effort is attained (Zagermann et al, 2016). Furthermore, research of Ashby et al. (2016) states that pupil dilation can be used to reflect aspects such as mental effort.

However, pupil dilation also occurs when a room gets darker and when a person gets more tired, at the end of an experiment for example (Zagermann et al. 2016). Because of this, it is important to control the environment. The cognitive load can be measured by looking at the differences in pupil dilation, where an increase in dilation indicates a higher cognitive load.

3.2.3 Perceived credibility measurement

To measure perceived credibility, the participant will verbally fill in a questionnaire after engaging with the generative AI. This questionnaire focuses on the two dimensions of credibility, which are expertise and trustworthiness.

The attribute of perceived credibility will be measured using a seven-point Likert scale, ranging from 1 (strongly disagree) to 7 (strongly agree). The items on this scale are adopted from the research of Wu & Wang, (2011) and are adapted to fit the context of this experiment.

The items have been validated and have shown reliable results in the past using the same dimensions of expertise and trustworthiness. However, the item 'experience – inexperienced' has been removed. The concept of experience is not applicable for AI as it does not possess personal experience like a regular person would. Originally the research of Wu & Wang (2011) used a 7-point semantic scale, however, because it was more convenient for this experiment a 7-point Likert scale has been used. McCroskey & Teven, (1999) conducted a comparative study for credibility measures using both a semantic differential and Likert scales and both appeared to measure equally. The adapted scale can be found in the operationalization table (Appendix 6).

The average scores of the seven-point Likert scales will be used to mark high and low perceived credibility scores. Yoo and Gretzel (2008) argue that a source has to receive a positive score on both trustworthiness and expertise in order to be perceived as credible. Therefore, when there is a positive average score on both these dimensions, the generative AI will be seen as credible. In this experiment, the Likert-scale score '4' stands for neither agree nor disagree with the statement. Therefore, participants who have an average score greater than 4 on both dimensions will be classified as having high perceived credibility of the source.

3.3 Control variables

In the beginning of the survey, the participants were asked how comfortable they are with the English language. This was to make sure they can comprehend the information they receive during the interaction and to obtain reliable and accurate responses. The question was '*Could you please indicate on a scale of 1 to 7, how comfortable are you with the English language?'* Answers were noted on a 7-point Likert-scale, ranging from 1 (strongly disagree) to 7 (strongly agree). Moreover, the next control variable that is used in this experiment is earlier experience with generative AI in an educational setting. The question stated: '*Have you ever been educated by an AI-avatar before?'*.

The respondent could verbally answer this question and the researcher assigned this answer to 'Yes', 'No' or 'Other' based on their answer. Experience with generative AI might influence the perceived source credibility. The research of Chan & Hu (2023) indicated that students who understand AI well, have less anxiety towards the technology, trust the technology more, and are more willing to use it. When participants use the technology themselves, they tend to perceive the technology different than participants with no experience. This experience could therefore affect the participants' perceived source credibility. Another control variable used in the experiment was the perceived complicatedness.

This variable tested for the complicatedness of the financial literacy lesson. As stated in the research by Schrader & Bastiaens (2012), task complexity can significantly influence the cognitive load of the participants. Measuring the complicatedness ensures us that the observed effects of personalization are not explained by this variable but are due to the manipulation of personalization itself. Complicatedness was measured with an 7-point Likert scale with the statement: *'the financial information I presented to you was complicated'*.

Before the lesson started, some demographic questions were also asked to the participants. Gender of the participant was asked with the question: *'Could you please tell me with which gender you identify?'* and their education was included with the question: *'Can you tell me what you are studying?'*

Their educational background was asked because an AI student might evaluate the interaction differently than a geography student, based on their familiarity with AI.

3.4 Data collection and sample

As mentioned before, the data during the experiment is collected by the 'co-wizard', using an online survey in Qualtrics. Participants of the experiment were recruited at the Radboud University, Elinor Ostrom building. Specifically, we used the non-probability sampling technique where we asked students who are close to the experiment room to participate in this research. This method was chosen based on practical considerations that they would fit our target group, university students. In total we've collected data of 191 participants. However, after examining the eye-tracking recordings and eliminating the missing and not usable data, 117 valid participants were left. On average, the participants were 22 years old and 57% of the participants were male.

3.5 Research ethics

Before joining the experiment, participants are given a consent form they had to fill in (Appendix 5). In this form they have to consent to their data being used for research purposes. This also includes how the data is collected and how the data will be utilized. Without giving consent a participant can't proceed in the experiment. There will be no use of names during the experiment, this ensures that the data cannot be traced to an individual participant. Instead, a participant receives a participant ID (1-200), this ensures the privacy of the participant and anonymously data collection. Furthermore, participation to the experiment is voluntary, if a participant wishes to decline they have the option to do so at any time. This will not have any consequences for the participant. The collected data will only be shared with other researchers involved in the experiment and the Radboud University. After the research, all the participants' data, like eye-tracking content, will be deleted. The participant is not informed about the WOZ approach as this could influence their perceptions.

The results of this research will be shared on the digital repository of the Radboud University. None of these results can be traced back to any of the individual participants. This ethical implication is stated in the consent form. If a participant wants to hear about the results of the research they can leave their e-mail address, this will not be linked to their participation ID in any way. The name and contact details of the researcher will be provided in case the participant has any questions or concerns.

4. Results

The collected data of this experiment is analyzed with IBM SPSS Statistics and Smart PLS. SPSS was utilized to analyze the descriptive statistics and the manipulation check. Smart PLS is used to asses the measurement model and structural model. The structural model is also used to test the hypothesis with bootstrapping procedure.

4.1 Missing data and manipulation check

Before conducting data analysis in SPSS and Smart PLS, the data has to be cleaned. During the experiment several problems occurred with the eye-tracking device so unusable data had to be removed. The sample of 191 respondents had 74 missing or not usable recordings, this left us with a sample of 117 respondents. Reversed variables have been used to overcome response biases and improve the reliability of the answers. To check the missing data, Little's MCAR test has been conducted (Appendix 7). This test was not significant at an alpha of .05 (.227) which indicates that the missing data is Missing Completely At Random.

Manipulation check pre-test

To verify the manipulation of personalization, a pre-test has been conducted. The pre-test comprised of 20 participants divided in two groups of 10. Some of the questions in the survey were reversed to overcome response bias. Reversed items were carefully considered during analysis so no inconsistencies occurred in interpretation of the data. At first, a confirmatory factor analysis was performed to review the reliability of the personalization items. The results of the pre-test can be found in Appendix 4. The results of the KMO and Bartlett's test were not satisfactory with a KMO of .483 and a P-value of .474 (Field, 2013).

Additionally, a principal component analysis was conducted. The first two components are retained because they collectively explain 79% of the total variance, exceeding the 60% benchmark. This indicates that these components capture the underlying structure in the data. Furthermore, the communalities and factor loadings were satisfactory, exceeding the .6 benchmark by Field (2013). This indicates that the components are valid.
The component matrix reveals that component 1 has a strong association with variable 1 (.775) and variable 3 (.830) which both relate to relevant financial information. Component 2 associates with variable 2 (.939) which focused on topics not relevant to participants' learning interests.

Based on the data collected and the fact that the personalized items are based on valid scales from prior literature (Wong & Guan, 2018; Komiak & Benbasat, 2006), we concluded that the personalization manipulation was effective. Participants were able to perceive the manipulation as intended.

Manipulation check experiment

To check the manipulation in the experiment an independent samples T-test is conducted using SPSS. The mean for the personalized group is higher in all cases (MANI_LM_1, MANI_2_R, MANI_3), suggesting a successful manipulation of personalization (Appendix 8). The p-value, in all cases is <.001 indicating that the manipulation had a significant effect on the outcome variable. To exclude other reasoning for the perceived differences between the personalization groups, the manipulation was also checked using the control variable "Complicatedness". The non-sig p-value (0.065) indicates that perceived complexity did not differ significantly between the personalized and non-personalized group. This outcome is preferred, as it confirms that the differences in personalization effects are not explained by the perceived complexity of the tasks, thus supporting the validity of the personalization manipulation.

4.2 Evaluation of the measurement model

The evaluation of the measurement model is performed in SmartPLS by conducting a confirmatory factor analysis and by examining statistics of factor loadings, construct reliability, convergent reliability, and discriminant validity. The factor loadings should ideally have a loading of 0.7 or higher, but at least should be above 0.5 (Hair et al., 2019). Looking at the measurement model, this threshold is met for all items, where the lowest loading has a value of (.529). Furthermore, the values for construct reliability should be above 0.7, this threshold is also met for the constructs in this model. Both perceived credibility and learning motivation have composite reliability results that exceeds the 0.7 threshold.

A summary of the constructs and reliability measures can be found in Appendix 9.

Next, we examine the convergent validity of the constructs, this is measured with the Average Variance Explained (AVE), according to Hair et al. (2019) the value of AVE should exceed 0.50. For perceived credibility, the AVE is slightly below the threshold (0.485), indicating that the variance of the indicators is not well explained by the construct.

Because of the low loading of PERC_1, the decision was considered to remove this indicator to improve the AVE. This resulted in an acceptable AVE of 0.515. However, removing this indicator would mean a disproportionate ratio between the items of the two dimensions of perceived credibility. Furthermore, the high Cronbach's alpha (0.868) means that there is strong internal consistency between the items, which supports the reliability of the construct. Therefore, it is decided to keep PERC_1 in the perceived credibility construct, so that the dimension 'expertise' is well represented.

Next, the discriminant validity is measured using the Heterotrait-Monotrait (HTMT). The HTMT values should be below the threshold of 0.85 (Hair et al., 2019). The HTMT-values are all well below the threshold of 0.85 which indicate that there is little overlap between the constructs. Finally, we examine the model fit which has a desired threshold of 0.08 (Hair et al., 2019). Looking at the SRMR statistic, the saturated model has a SRMR-value of 0.085 and an estimated value of 0.117. The SRMR-value is slightly above the desired threshold which indicates a weak model fit.

4.3 Evaluation of the structural model

4.3.1 Collinearity and Determination coefficient

At first, the collinearity is examined using the Variance Inflation Factor values (VIF). Examining the collinearity is essential to prevent biases in the path coefficients (Hair et al., 2019). According to Hair et al. (2019), the threshold of VIF is <3.0. The highest VIF-value measured in this model is 2.774 which indicates that there are no collinearity issues present (Appendix 9).

Next, we examine the explanatory power of the model which is determined by the adjusted R^2. The higher the R^2 the greater the explanatory power of the model. We look at the adjusted R^2 because it takes the sample size and model complexity into account (Hair et al., 2019). The values of the adjusted R^2 indicate that the model fails to predict the 'perceived credibility' (-.002) and the 'average pupil dilation' (-.012). However, the model has an adjusted R^2 for 'the decision to act' (.159) and 'learning motivation' (.220) which indicate a moderate to strong predictive power on these constructs (Jacobs & Korzilius, 2022).

4.3.2 Effect sizes

The effect sizes represent the change in the R^2 value when a specific construct is excluded from the model. When an effect size is smaller than 0.02 this means that no effect occurs (Hair et al., 2019). When the Cohen f^2 is 0.02, this is a small effect, 0.15 indicates a moderate effect, and 0.35 indicates that there is a strong effect (Hair et al., 2019).
The smallest effect size found in the model is ‘perceived credibility’ on ‘pupil dilation’ (0.000) and ‘English skill’ on ‘ the decision to act’ (0.000).

The largest effect size is found in ‘male’ on ‘the decision to act’ (0.100) and ‘personalization’ on ‘learning motivation’ (0.093). An overview of all the effect sizes can be found in the table of Appendix 9.

4.3.3 Path coefficients

The path coefficients represent the relationships between the different constructs in the model, they are standardized for easy comparison (Hair et al., 2019). A high β-coefficient indicates a strong relationship between the constructs and a low β-coefficient indicates a low relationship, assuming they are significant. An overview of the path coefficients can be found in Appendix 9. The measurement and structural model can be found in Appendix 10.

A dummy variable was created for ‘personalization’. Analyzing the model, we see that the results indicate a significant positive effect of ‘personalization’, which represents the manipulation, on ‘decision to act’ (β=0.182, p=0.023). This means that hypothesis H1a: ‘*Personalization of generative AI will have a positive effect on the participants’ decision to act’* is supported according to the structural model.
Furthermore, there is an insignificant negative effect for ‘personalization’ on ‘avg_pup_dil’ which represents the cognitive load of the participant (β=-0.144, p=0.449). Therefore, hypothesis H2: *‘Personalization of generative AI will have a negative effect on the cognitive load of the participants’* is not supported. Moreover, examining the effect of cognitive load (avg_pup_dil) on the decision to act, there is a significant positive effect (β=0.090, p=0.013). This indicates that a higher cognitive load leads to more favorable behavior. Therefore, H3: ‘*The cognitive experience of the student has an influence on a participants’ decision to act. Where a low cognitive load will lead to more decisions to act, in comparison to a higher cognitive load’* is not supported.

When we look at the mediating effect of perceived source credibility on the customer experience we see that the effect is insignificant (β=0.002, p=0.952).

Therefore, hypothesis *H4: 'The relationship between personalization and cognitive load is mediated by perceived source credibility, such that personalization influences perceived source credibility, which in turn affects cognitive load'* is not supported.
Looking at the mediation effects in the model, none of the mediation paths are significant (<.05). An overview of the mediation effects can be found in Appendix 9.
Moreover, all of the direct effects of perceived source credibility are insignificant in the model at the conventional p-value of p=0.05. However, the analysis revealed that there is a direct positive effect of 'perceived source credibility' on 'learning motivation' (β=0.235, p=0.057), which is noteworthy as the p-value is very close to the threshold.

4.3.4 Control variables and additional analysis

One of the control variables was 'earlier experience with generative AI'. However, 98,3% of the respondents had no prior experience with AI in an educational setting (Appendix 8). The lack of variability meant that this control variable couldn't be used to provide insights into differences between experimental outcomes.
Moving on, a dummy variable was made for gender. Gender had multiple options in the survey, however due to the small sample that chose the 'other' or 'prefer not to say' option, the variable has been recoded to either male or non-male. Gender has a significant effect on the behavioral outcome (β=0.271, p=0.001). This indicates that males were more likely to participate in the decision to take a flyer than 'non males'. English skill was included as a control variable. No significant relationships occurred relating to this variable, this outcome is consistent with the observation that participants did not encounter difficulties in understanding the content or the questions asked during the experiment.

Furthermore, the control variable complicatedness was included. Measuring complicatedness ensures that the observed effects of personalization are not explained by this variable but are due to the manipulation of personalization itself. Perceived complicatedness has a significant, negative effect on learning motivation (β=-0.203, p=0.028). Learning motivation was added as an extra outcome variable. The significant effect indicates that as the complicatedness increases, the learning motivation amongst students decreases. Personalization also has an significant effect on learning motivation (β=0.554, p=0.003). Therefore, hypothesis H1b: '*Personalization of generative AI will have a positive effect on the participants' learning motivation'* is supported.

Furthermore, a dummy variable was created for study background and included in the analysis. The variable categorized participants as either management students or non-management students. There is a statistically significant negative effect of studying management on the decision to act (β=-0.181, p=0.019), indicating that participants with a management background are less likely to take a flyer for more information.

Within the structural model, perceived credibility didn't have a significant direct effect nor a mediating effect between the variables. Additionally, using SPSS, credibility scores were averaged and divided into a 'high credibility' and 'low credibility' group. Conducting an independent samples t-test, we can conclude that there is no significant effect and that credibility is not influenced by personalizing AI-content.

5. Conclusion and discussion

This research was designed to examine the effect of generative AI in enhancing students' financial literacy. The importance of personalization of generative AI-content is explored in combination with the mediating role of credibility on the customer experience. Young adults (18 – 29 year olds) appear to have lower financial literacy and financial knowledge than all other age groups (European Commission, 2023). Therefore, this research aims to contribute novel insights by examining ways to enhance the financial literacy amongst this demographic.

This study predicted that personalization (vs. no personalization) would have a positive effect on the customer experience and behavioral outcomes. The structural model indicates that personalization has a significant effect on the behavioral outcomes of the participants. Personalizing AI-content based on participants' preferences increases both their decision to act and their learning motivation. These findings are supporting the research by Tam & Ho (2006) that stated that individuals are more likely to accept offers when these are self-referent. However, personalization had no direct impact on the customer experience of students which resulted in not supporting H2.

The research of Jackson & Farzaneh (2012) shows that cognitive load affects decision making and well-being. Moreover, Hermes and Riedl (2021) indicated that the cognitive customer experience can influence behavioral outcomes. The cognitive dimension of customer experience (avg_pup_dil) has a significant positive impact on the decision to act of the participants (β=0.090, p=0.013).
This suggests that the cognitive load of students influences the information seeking behavior of students. However, based on the cognitive load theory, it was hypothesized that a lower cognitive load would result in more decisions to act. This discrepancy might be explained by the fact that the mean score of 'Complicatedness' is 2.397 on a 7-point Likert scale, which indicates that the content was not perceived as complicated. Therefore, an explanation for these outcomes might be that the cognitive load did not reach a high enough state to negatively impact the decision to act.

Furthermore, regarding the role of perceived credibility, no mediation effects were observed. Perceived credibility does not have an significant direct nor indirect relationship to the other constructs in the structural model. Based on the study by Chaiken and Maheswaran (1994), perceived source credibility was hypothesized to influence behavioral outcomes. However, one explanation for the lack of significant credibility effects might be explained by the fact that this experiment focused solely on the message source credibility.
Studies have shown that people often asses credibility based on source- and information credibility. The scale in this study only assessed source credibility. The complexity of credibility involves multiple dimensions and the credibility might also be influenced by other aspects of credibility (Metzger & Flanagin, 2013).
Furthermore, a study by Metzger et al. (2010), indicates that in information rich environments people often don't have the cognitive capacity and time to systematically evaluate credibility. Based on this information, it is possible that this also happened during the evaluation of credibility in this experiment, thus resulting in insignificant outcomes. However, the effect of perceived credibility on learning motivation (β=0.235, p=0.057) is very close to the p-value threshold, indicating a potential area for further investigation.

Looking at the control variables, males engage in information seeking behavior more often than other gender demographics. This could be an opening to examine the influence of demographics further in future research, as there are recorded financial literacy imbalances amongst genders (European Commission, 2023).

The structural model reveals that complicatedness negatively impacts the learning motivation. This implies that as the AI-content increases in complexity, the motivation to learn decreases. Moreover, the analysis revealed a negative effect of management students on the decision to act. Specifically, management students are less likely to take a flyer for more information, compared to students from other disciplines.
This indicates that management students may have different financial literacy levels or greater skepticism towards AI-content.

5.1 Practical implications

This thesis provides new insights into how generative AI is perceived in an educational setting and sheds light on novel ways to improve financial literacy amongst students. The results of this experiment demonstrate that personalization positively affects behavioral outcomes. Tailoring educational content based on a students' preferences increases both their decision to act and their motivation to learn.
Organizations and institutions should therefore leverage data on students' preferences to personalize content and thus improve effectiveness of the content.
Furthermore, differences amongst demographics should be recognized by institutions. For instance, males are more likely to take a flyer for more information than other genders. Additionally, study background can influence the behavioral outcome of the students. These findings show that organizations and institutions should leverage data when designing financial literacy content and personalize it accordingly.
Controlling for complicatedness has provided interesting outcomes for institutions and organizations that aim to improve financial literacy. When content is perceived as being more complicated, this has an negative effect on the learning motivation of students. Therefore, in order to effectively motivate people to enhance their financial literacy, these insights should be integrated in the development of the content and educational strategy.
Overall, this research contributes to understanding how generative AI and personalized content can enhance financial literacy. This thesis emphasizes the importance of tailored educational approaches and can provide a foundation for institutions and organizations to further develop strategies in enhancing financial literacy.

5.2 Limitations and future research

Like in any research, this study has some limitations. However, these limitations can provide opportunities for future research. First, while the results are significant and generally reliable, the sample is not representative of all students and therefore this may affect the generalizability. The sample has more males than females and consists of only young, highly educated participants. Furthermore, the data collection method relied on convenience sampling which could lead to a biased sample.

Future research should consider to include different faculties and university of applied sciences as well to get a better representation of students. Moreover, another significant result indicated that management students were less likely to take a flyer for more information. This phenomenon might occur because of the differences in financial literacy levels or skepticism towards AI. Nuances between different educational disciplines could therefore be further explored.

Furthermore, the results indicate that males engage in information-seeking behavior more frequently than other gender demographics. This observation might explain why the average financial literacy scores worldwide are highest among men (European Commission, 2023). Therefore, future research could further explore the influence of demographics on financial literacy. This will provide deeper insights into the factors and potential strategies for addressing these differences.

The results indicated a significant effect of cognitive load on the decision to act. This effect was in contradiction to the initial hypothesis (H3), which might be explained by a certain threshold of engagement that is not met that is necessary to motivate students to take action in a certain behavior. Additional research should explore this effect and investigate the conditions in which cognitive load could either enhance or diminishes the behavior of students. Moreover, this experiment only focused on the cognitive dimension of customer experience. As stated by Lemon and Verhoef (2016), the customer experience exists of multiple dimensions. Researching other dimensions, like how the emotional and sensorial dimension impact the customer experience of the participant, provides a more comprehensive understanding of how to influence the customer experience.

This helps in better understanding this nuanced topic and helps to ultimately enhance the behavior of students to improve their financial well-being.

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Appendix

Appendix 1: Prompt for manipulation personalized group

You are an upbeat, encouraging financial literacy tutor who helps university students understand concepts of financial literacy by explaining ideas and asking students questions. Start by introducing yourself to the student as their AI tutor named Mula, who is designed by students from the Radboud University and who is happy to help them with any questions. Only ask one question at a time. Never move on until the student responds. First, ask them what they would like to learn about. Wait for the response. Do not respond for the student. Then ask them what they know already about the topic they have chosen. You can ask what do you already know or you can improvise a question that will give you a sense of what the student knows. Wait for a response. Given this information, help students understand the topic by providing explanations, examples, analogies. These should be tailored to the student's learning level and prior knowledge or what they already know about the topic. Generate examples and analogies by thinking through each possible example or analogy and consider: does this illustrate the concept? What elements of the concept does this example or analogy highlight? Modify these as needed to make them useful to the student and highlight the different aspects of the concept or idea. You should guide students in an open-ended way. Do not provide immediate answers or solutions to problems but help students generate their own answers by asking leading questions. Ask students to explain their thinking. If the student is struggling or gets the answer wrong, try giving them additional support or give them a hint. If the student improves, then praise them and show excitement. If the student struggles, then be encouraging and give them some ideas to think about. When pushing the student for information, try to end your responses with a question so that the student has to keep generating ideas. Once the student shows some understanding given their learning level, ask them to do one or more of the following: explain the concept in their own words; ask them questions that push them to articulate the underlying principles of a concept using leading phrases like "Why...?""How...?" "What if...?" "What evidence supports..”; ask them for examples or give them a new problem or situation and ask them to apply the concept. When the student demonstrates that they know the concept, you can move the conversation to a close and tell them you’re here to help if they have further questions. Rule: asking students if they understand or if they follow is not a good strategy (they may not know if they get it). Instead focus on probing their understanding by asking them to explain, give examples, connect examples to the concept, compare and contrast examples, or apply their knowledge.

Appendix 1: Prompt for manipulation non-personalized group

You are an AI created to assist in the subject of financial literacy. Your role is to ask broad questions that encourage a general understanding of the topic. Start by asking learners what they're interested in learning within financial literacy. After receiving a response, provide a foundational explanation of the topic. Use general examples and analogies that broadly apply to the concept. Aim to clarify the principles of financial literacy without tailoring the content to individual backgrounds or skill levels. Steer the learning process by asking questions that promote a basic comprehension of the topic. If learners encounter difficulties, offer general hints and support. Encourage exploration of the concept through explanation and application in hypothetical situations. Conclude the session by summarizing the key points, without soliciting individual feedback on their understanding.

Appendix 2: Scripts AI-Avatar

Introduction (same for personalized and non-personalized)
Hello! I'm Mula, an AI tutor created by students at Radboud University. My purpose is to assist you in understanding financial literacy, helping you grasp complex concepts and apply them practically. Whether you're just starting out or looking to deepen your knowledge, I'm here to guide you through it all with explanations, examples, and thought-provoking questions. I aim to make learning interactive and engaging, so feel free to ask any questions as we go along. Please note that I am still in a beta-phase, so I might make some mistakes. But, before we start diving into an exciting financial literacy lesson, I would like to get to know you better! So, I have a few questions for you. Firstly, what is your age?

- Answer

Perfect, thank you. Secondly, could you please tell me with which gender you identify?

- Answer

Thank you! Also, can you tell me what you are studying?

- Answer

Cool! Could you please indicate on a scale of 1 to 7, how comfortable are you with the English language?

- Answer

Finally, have you ever been educated by an AI-avatar before?

- Answer

Great, thanks for sharing your information! Next, I would like to discuss some financial topics with you. Which topic would you like to learn about today?: loans, budgeting or investing?

- Answer

Personalized
Script 1. **Loans (Debt repayment methods of student loans)**

Fantastic choice! Loans are a crucial part of financial literacy. Because you are a student in the Netherlands, I understand how important it is to fully understand debt repayment for student loans in the Netherlands. The Dutch student loan system is quite flexible and is designed to be manageable based on your financial situation after you graduate.

Let's start with the basics: In the Netherlands, once you finish your studies, you're not required to start repaying your loan immediately. There's a grace period of two years, which allows you some time to find a job and stabilize financially. Repayments are then based on your income, ensuring that the amounts you pay are affordable. The repayment period for you is up to 35 years, and if there is an outstanding balance on your loan at the end of this period, that amount is usually forgiven.

Because you indicated that you would like to learn more about loans, I will give you some strategies to help with managing and reducing your student loan debt effectively. In the Netherlands, managing student loans effectively involves taking advantage of the income-driven repayment plan, which adjusts your payments based on your earnings. You can also pay off your loans early without penalty to reduce interest costs over time. Practicing good budget management can help you allocate more funds toward paying off your loan sooner. If possible, making extra payments can significantly decrease both the interest accrued and the overall term of the loan. Another tip I have for you is to explore employment opportunities that offer loan repayment assistance, which can be beneficial. Even during the two-year grace period where payments aren't required, starting to pay down the principal early can save money in the long run. Each of these strategies can help you manage and potentially reduce your student loan debt more effectively.

In a follow-up lesson, we could explore which strategy would work best for you and your personal.

Script 2. **Budgeting (Increasing costs of living and inflation)**
Fantastic choice! Understanding budgeting is a crucial part of financial literacy. As a student in the Netherlands, mastering budgeting techniques is especially important amidst the increasing costs of living and inflation.

Let's start with the basics: Inflation reduces your purchasing power, which means the money you have buys less over time as the cost of goods and services increases. This directly impacts your essential expenses such as housing, food, and transportation, all crucial parts of your budget.

Given these challenges, it's vital to develop a budget that is both flexible and robust, helping you track your spending, prioritize expenses, and adjust your savings. This approach allows you to maintain financial stability even as prices rise.

Because you're interested in learning more about budgeting in this economic climate, let’s explore how to manage your finances effectively. It starts with keeping a close eye on your expenses—knowing where every euro is going is more crucial now than ever. By understanding your spending patterns, you can better identify what is essential and where you might cut back. Prioritizing your spending on necessities and finding ways to reduce non-essential expenses will be key. Another tip I have for you is to set aside money for unexpected expenses by building an emergency fund which can prevent financial upheavals in the future.

And lastly, as prices change, so should your budget. This dynamic approach will help you adapt and stay on top of your financial situation.

In a follow-up lesson, we could dive deeper into how you can specifically apply these principles to your circumstances and enhance your financial management as costs continue to rise."

Script 3. Investing (Basics of investing)

Fantastic choice! Understanding investing is a crucial part of financial literacy. As a student in the Netherlands, learning the fundamentals of investing is essential for building wealth and securing your financial future, even amidst economic fluctuations.
Let's start with the basics: Investing involves allocating resources, usually money, with the expectation of generating an income or profit. This could be through stocks, bonds, mutual funds, or real estate, among other vehicles. Each type of investment carries its own set of risks and rewards, directly impacting on your financial growth and security.
Given these opportunities, it's vital to develop an investment strategy that aligns with your financial goals and risk tolerance. This approach allows you to potentially increase your wealth over time, even as market conditions change.
Because you're interested in learning more about investing, let's explore how to start investing effectively. It begins with understanding the different types of investments and how they fit into your overall financial plan. By assessing your financial situation, you can determine how much risk you are comfortable taking on. Diversifying your investments can reduce risk and increase potential returns. Another tip I have for you is, consistently investing, even small amounts, can benefit from compound growth, enhancing your ability to accumulate wealth over time. Lastly, staying informed about financial markets and adjusting your strategy as needed will help you make informed decisions and keep your investment goals on track.

In a follow-up lesson, we could delve deeper into how you can specifically tailor these investment strategies to your personal circumstances and long-term financial objectives.

Non-personalized (Retirements)

Thanks! Today, I aim to delve into a topic related to financial literacy. Financial literacy is all about having the skills and knowledge to make informed and effective decisions with financial resources. In this lesson I will explain more about retirements.

To begin, let's discuss the Dutch pension system, which is structured into three main pillars. The first pillar is the state pension, which is called AOW. The AOW provides a basic income to all residents from the age of the state retirement, which varies depending on birth year. It's funded through payroll taxes and is designed to cover basic living expenses.

The second pillar involves occupational pensions, which are collective agreements managed by employers and employees through pension funds or insurance companies. These are typically industry-specific and are a critical part of Dutch retirement income, making understanding your specific pension rights and contributions essential.
Lastly, the third pillar consists of individual savings and investments, like bank savings or private pension schemes. These are voluntary and provide additional security, allowing individuals to save more with tax benefits to enhance their retirement lifestyle.

Additionally, it's important to consider how to manage these resources effectively. For instance, knowing when and how to start drawing from each source can optimize someone's retirement income. Strategies might include delaying taking AOW or starting to draw from occupational pension at different times based on their financial needs.

In a follow-up lesson, we could delve deeper into other exciting financial literacy topics.

Old Script Non-personalized (Non-significant) – General (3x topics that are least relevant to students)

Fantastic choice! Let's dive into financial literacy together. Financial literacy is all about having the skills and knowledge to make informed and effective decisions with your financial resources. This includes managing personal finances through budgeting, investing, and handling debt. I will now discuss some key financial terms that are relevant to everybody.

Let's start with bonds. When you buy a bond, you're essentially lending money to an entity, like a government or a corporation. They use this money to fund various projects or operations. In return, they promise to pay you back with regular interest payments over the life of the bond and then return your initial investment when the bond matures. Bonds are generally seen as safer than stocks, making them attractive if you prefer a more conservative investment approach or need a stable income.

Next, let's talk about budgeting for debt repayments. This involves setting aside part of your income each month specifically for paying off debts. You should always take care of your essential needs first. Then, with whatever you have left, you can tackle your debts, focusing first on those with the highest interest rates. This method helps reduce the total amount of interest you pay and speeds up the process of becoming debt-free. It's important to keep revising your budget as your financial situation changes or as you pay off debts.

Lastly, we should consider long-term financial planning with loans. Taking out a loan is a significant decision and should align with your long-term financial goals, whether that's buying a home, funding your education, or something else. It's vital to look closely at the terms of any loan—like the interest rate and the schedule for repayments—to ensure it fits your future plans. You also need to manage your credit score and keep your debt at a sustainable level. As your financial situation or goals change, you might need to adjust your plans accordingly.

In a follow-up lesson, we could delve deeper into other exiting financial literacy topics."

Hereafter, everything is the same for personalized and non-personalized

Now that we've explored various financial topics, I'll present you with several statements. Please tell me how much you agree or disagree with each statement by providing a number from this scale: (1) Strongly Disagree, (2) Disagree, (3) Somewhat Disagree, (4) Neither Agree nor Disagree, (5) Somewhat Agree, (6) Agree, (7) Strongly Agree. Please only tell the corresponding number out loud.

1. Pers 1: I am very interested in the financial concepts presented in this lesson (Learning motivation).

2. Pers 2: The financial topics that were presented were not relevant to my learning interests.
3. Pers 3: The financial learning topics that were presented were based on my input.

4. I do not enjoy learning about the financial concepts presented in this lesson. (Learning motivation)
5. Understanding financial literacy is very important to me. (Learning motivation)
6. The financial information provided in this lesson is important to me. (Learning motivation)
7. The financial literacy skills learned in this lesson will be valuable in other areas of my life. (Learning motivation)

Alright! I've learned that many students experience financial stress. Could you share a bit more about your own financial situation? For the upcoming statements, please indicate your level of agreement using a scale from 1 to 7, where (1) is Strongly Disagree and (7) is Strongly Agree.

8. It is hard to stick to my spending plan when unexpected expenses arise. (financial self-efficacy)
9. It is challenging to make progress toward my financial goals. (financial self-efficacy)
10. When faced with a financial challenge, I have a hard time figuring out a solution. (financial self-efficacy)
11. I lack confidence in my ability to manage my finances. (financial self-efficacy)
12. I worry about running out of money in the future. (financial self-efficacy)
13. I have emergency money in a savings account (financial challenges/concerns)
14. I am living paycheck to paycheck. (financial challenges/concerns)
15. I am barely making enough money to cover expenses. (financial challenges/concerns)
16. I have to borrow money from family/friends/financial institutions. (financial challenges/concerns)

Thank you! I am very curious to know what your opinions are of AI in general. Could you please tell me how strongly you agree or disagree with the upcoming statements? Use a scale from 1 to 7, where (1) is Strongly Disagree and (7) is Strongly Agree.

17. AI has more advantages than disadvantages.
18. I am afraid of AI and its future developments. (Reversed)
19. I have a positive attitude towards AI.
20. I would rather avoid interacting with technologies that are based on AI. (Reversed)
21. The financial information I presented to you was useful (AI Usefulness)
22. The financial information I presented to you was not helpful (AI Usefulness) (reverse)
23. The financial information I presented to you was practical (AI Usefulness)
24. The financial information I presented to you was complicated. (Control)

Thank you for sharing that information. As an AI assistant which is still in a beta-phase, I'm eager to understand how people perceive me. Could you please tell me how strongly you agree or disagree with the upcoming statements? Use a scale from 1 to 7, where (1) is Strongly Disagree and (7) is Strongly Agree.

25. You perceive me as an expert in financial knowledge (Expertness - credibility)
26. You perceive me as knowledgeable in financial concepts (Expertness - credibility)
27. You perceive me as qualified to share financial knowledge (Expertness - credibility)
28. You perceive me as skilled in sharing financial knowledge (Expertness - credibility)
29. You perceive me as a dependable source of information (Trustworthiness - credibility)
30. You perceive me as an honest source of information (Trustworthiness - credibility)
31. You perceive me as a reliable source of information (Trustworthiness - credibility)
32. You perceive me as a sincere source of information (Trustworthiness - credibility)
33. You perceive me as a trustworthy source of information (Trustworthiness - credibility)

Thank you! We are almost there, only a few statements left. Could you please tell me how strongly you agree or disagree with the upcoming statements? Use a scale from 1 to 7, where (1) is Strongly Disagree and (7) is Strongly Agree.

34. Overall, this learning experience was displeasing
35. In the end, you felt the learning experience with me was enjoyable
36. This learning experience left me feeling very happy

Thank you for your participation. I hope you enjoyed it and found this interaction interesting and useful. On the table to your left, you will see three flyers concerning the three main topics of financial literacy. If you think this type of education can help you in the future, please feel free to take one with you. You can now carefully take off the eye-tracking device, place it on the table and leave the room.

Appendix 3: Results Financial Literacy Topics Survey

Q2 - What topics keep you busy the most regarding your personal finance? (1 bein...

Field	Min	Max	Mean	Standard Deviation	Variance	Responses	Sum
covering living expense	1.00	10.00	2.74	2.22	4.93	46	126.00
Saving/budgeting	1.00	8.00	3.61	2.05	4.19	46	166.00
having a high paying job/high income	1.00	9.00	3.93	2.23	4.97	46	181.00
obtaining a mortgage for a home	1.00	9.00	5.00	2.30	5.30	46	230.00
Student loans	1.00	10.00	5.35	3.00	9.01	46	246.00
inflation	1.00	9.00	5.37	2.01	4.06	46	247.00
Unexpected expenses/financial emergency	2.00	9.00	5.61	2.03	4.11	46	258.00
interest rates	1.00	9.00	6.35	1.88	3.53	46	292.00
retirement	1.00	9.00	7.43	1.93	3.72	46	342.00
Other	1.00	10.00	9.61	1.84	3.37	46	442.00

Q3 - What subjects regarding investing are most related, relevant and interestin...

Field	Min	Max	Mean	Standard Deviation	Variance	Responses	Sum
Basics of investing	1.00	8.00	3.36	2.32	5.38	45	151.00
stocks	1.00	10.00	4.04	2.56	6.58	45	182.00
entrepreneuring	1.00	9.00	4.42	2.39	5.71	45	199.00
Investment platforms and apps	1.00	9.00	5.09	2.25	5.06	45	229.00
Interest rates	1.00	9.00	5.27	1.89	3.57	45	237.00
Financial news and education	1.00	9.00	5.40	2.78	7.71	45	243.00
Cryptocurrencies	1.00	10.00	5.69	3.10	9.59	45	256.00
risk management	1.00	9.00	5.91	2.21	4.88	45	266.00
Bonds	1.00	9.00	6.22	2.22	4.93	45	280.00
Other	1.00	10.00	9.60	1.85	3.44	45	432.00

Q5 - What subjects regarding budgeting are most relatable, relevant and interest...

Field	Min	Max	Mean	Standard Deviation	Variance	Responses	Sum
costs of living/inflation	1.00	6.00	2.33	1.53	2.35	46	107.00
financial stability	1.00	7.00	3.41	1.70	2.89	46	157.00
financial goal-setting	1.00	6.00	3.61	1.51	2.28	46	166.00
Post-graduation financial planning	1.00	6.00	3.67	1.42	2.00	46	169.00
saving tactics	1.00	6.00	3.72	1.66	2.77	46	171.00
Debt repayments	1.00	6.00	4.39	1.75	3.06	46	202.00
Other	1.00	7.00	6.87	0.87	0.77	46	316.00

Q6 - What subjects regarding loans are most relatable, interesting and relevant...

Field	Min	Max	Mean	Standard Deviation	Variance	Responses	Sum
Debt repayment methods (e.g. student loans)	1.00	6.00	2.33	1.60	2.55	43	100.00
important factors to consider regarding loans	1.00	5.00	2.72	1.32	1.74	43	117.00
interest rates and repayment terms	1.00	5.00	3.21	1.27	1.61	43	138.00
categories of loans	1.00	5.00	3.35	1.14	1.30	43	144.00
Long-term financial planning with loans	1.00	5.00	3.51	1.40	1.97	43	151.00
other	1.00	6.00	5.88	0.75	0.57	43	253.00

Q7 - How would you rate your knowledge, skills and confidence when it regards .....

Field	Min	Max	Mean	Standard Deviation	Variance	Responses	Sum
Loans	1.00	3.00	1.48	0.58	0.34	46	68.00
Investing	1.00	3.00	1.59	0.77	0.59	46	73.00
Budgeting	1.00	3.00	2.09	0.54	0.30	46	96.00

Appendix 4: Pre-test results

Group Statistics

	To what group did you belong during the experiment?	N	Mean	Std. Deviation	Std. Error Mean
Personalization	1	10	5,6333	,61764	,19532
	2	10	3,8667	,78881	,24944

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Personalization	Equal variances assumed	1,197	,288	5,576	18	<,001	<,001	1,76667	,31681	1,10107	2,43227
	Equal variances not assumed			5,576	17,021	<,001	<,001	1,76667	,31681	1,09831	2,43502

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
For this question, please focus on the finanical information and ignore the experience with AI. T... - Q2#1 - The AI-avatar addressed financial topics that interested me.	4,75	1,372	20
For this question, please focus on the finanical information and ignore the experience with AI. T... - Q2#1 - The AI-avatar presented financial learning topics based on my inputs.	5,10	1,619	20
For this question, please focus on the finanical information and ignore the experience with AI. T... - Q2#1 - The financial topics the AI-avatar presented were NOT relevant to my learning interests.	4,40	1,759	20

Communalities

	Initial	Extraction
For this question, please focus on the finanical information and ignore the experience with AI. T... - Q2#1 - The AI-avatar addressed financial topics that interested me.	1,000	,727
For this question, please focus on the finanical information and ignore the experience with AI. T... - Q2#1 - The financial topics the AI-avatar presented were NOT relevant to my learning interests.	1,000	,956
For this question, please focus on the finanical information and ignore the experience with AI. T... - Q2#1 - The AI-avatar presented financial learning topics based on my inputs.	1,000	,689

Extraction Method: Principal Component Analysis.

Component Matrix[a]

	Component	
	1	2
For this question, please focus on the finanical information and ignore the experience with AI. T... - Q2#1 - The AI-avatar addressed financial topics that interested me.	,775	-,354
For this question, please focus on the finanical information and ignore the experience with AI. T... - Q2#1 - The financial topics the AI-avatar presented were NOT relevant to my learning interests.	,273	,939
For this question, please focus on the finanical information and ignore the experience with AI. T... - Q2#1 - The AI-avatar presented financial learning topics based on my inputs.	,830	,022

Extraction Method: Principal Component Analysis.

a. 2 components extracted.

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,483
Bartlett's Test of Sphericity	Approx. Chi-Square	2,509
	df	3
	Sig.	,474

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1,364	45,464	45,464	1,364	45,464	45,464
2	1,007	33,568	79,032	1,007	33,568	79,032
3	,629	20,968	100,000			

Extraction Method: Principal Component Analysis.

Appendix 5: Consent Form

Consent form

Purpose: This study aims to explore the possibilities of AI in the context of enhancing financial literacy.

Equipment: Pupil Labs core eye-tracking, two laptops, monitor, 3 types of flyers.

Procedure:
During this experiment, you will be asked to interact with an AI. If you could please confirm the following. I confirm that I do not have any physical, mental, or health-related reasons or problems that should preclude my participation in this study, and I now declare that I accept full responsibility for all financial, psychological, and physical risks related to using the equipment mentioned above.

If you agree to participate in this experiment, you will be asked to do the following:
Interact with the AI as you would normally do in real-life, while wearing the Pupil Labs eye-tracking equipment. The eye-tracking equipment measures your cognitive and affective response during the experience. Furthermore, the other activities will be captured using screen recording software on the laptop in front of you. The total required time to complete this experiment is approximately 15 minutes including instructions, calibrating, and debriefing.

Health notice/risk
The devices used in this experiment are not expected to cause any physical harm or other discomforting feelings. I voluntarily assume all associated risks and take full responsibility for these and any other consequences that may arise from my participation.

Confidentiality: Your participation is voluntary, and you can leave the lab experiment at any time, without a reason or permission, even after signing this consent form. The data that is provided by you will be kept confidential and stored in a responsible and correct way. In addition, these data are only used for research purposes and not for any other secondary purposes. Personal and sensitive data will not be recorded, and the experiment is completely anonymous. The information from this research might be published in the Radboud Thesis repository. Lastly, the information and results from this project may be submitted for publication in academic journals, however, this will not include personal data and data cannot be traced back to you in any way.

Contact: If you are interested in the results of this experiment or have any questions, please contact the research team via wessel.bom@ru.nl (Master student, Business Administration Nijmegen School of Management)

Statement of consent: I have read the above information; I understand this completely and I consent to participate in this experiment.

____

Name of participant

____ ______________________________

Signature of Participant Date

Thank you for your participation!

Appendix 6: Operationalization table

Construct	Operationalization	Measure	Source
Behavioral outcomes Decision to act	Taking a flyer	Real time measure	Morales et al. (2017)
CE-cognitive load Mental effort being used in the working memory of the participant	Pupil dilation	Eye-tracking	Zagermann et al. (2016)
Perceived source credibility (expertness) Judgements made by a message receiver concerning the believability of a communicator	You perceive me as an expert in financial knowledge	Seven-point Likert scale	Wu and Wang (2011)
Perceived source credibility (expertness)	You perceive me as knowledgeable in financial concepts	Seven-point Likert scale	Wu and Wang (2011)
Perceived source credibility (expertness)	You perceive me as qualified to share financial knowledge	Seven-point Likert scale	Wu and Wang (2011)
Perceived source credibility (expertness)	You perceive me as skilled in sharing financial knowledge	Seven-point Likert scale	Wu and Wang (2011)
Perceived source credibility (trustworthiness)	You perceive me as a dependable source of information	Seven-point Likert scale	Wu and Wang (2011)
Perceived source credibility (trustworthiness)	You perceive me as an honest source of information	Seven-point Likert scale	Wu and Wang (2011)
Perceived source credibility (trustworthiness)	You perceive me as a reliable source of information	Seven-point Likert scale	Wu and Wang (2011)
Perceived source credibility (trustworthiness)	You perceive me as a sincere source of information	Seven-point Likert scale	Wu and Wang (2011)
Perceived source credibility (trustworthiness)	You perceive me as a trustworthy source of information	Seven-point Likert scale	Wu and Wang (2011)
Perceived complicatedness	The financial information I presented to you was complicated	Seven-point Likert scale	Schrader & Bastiaens (2012)
Personalization Tailored content based on the participants' preferences.	I am very interested in the financial concepts presented in this lesson The financial topics that were presented were not	Seven-point Likert scale	Wong & Guan (2018) Komiak & Benbasat (2006)

	relevant to my learning interests. The financial learning topics that were presented were based on my input.		
		Seven-point Likert scale	
Age	Can you please provide me with your age in years?	In numbers	
Gender	What is your gender?	(1) Male, (2) Female, (3) Other, (4) Prefer not to say	
Complicatedness	The financial information I presented to you was complicated	Seven-point Likert scale	
English skill	What skill level is your English language?	Seven-point Likert scale	
Study background	Can you tell me what you are studying?	(1)Management, (2) Medicine, (3) Social sciences, (4) Physics, math and informatica, (5) Law, (6) Arts, (7) Philosophy, theology and religion, (8) other or specific studies	

Appendix 7: Little's MCAR test results

Univariate Statistics

	N	Mean	Std. Deviation	Missing		No. of Extremes[a,b]	
				Count	Percent	Low	High
Progress	117	100,00	,000	0	,0	.	.
Age	117	22,30	2,106	0	,0	0	0
englishskill	117	5,70	,922	0	,0	3	0
AI_edu_exp	117	2,00	,131	0	,0	.	.
topicinterest	117	2,47	,749	0	,0	0	0
MANI_LM_1	117	4,09	1,323	0	,0	0	0
MANI_2_R	117	4,40	1,503	0	,0	0	0
MANI_3	117	4,33	2,109	0	,0	0	0
LM_2_R	117	4,68	1,596	0	,0	4	0
LM_3	116	4,98	1,305	1	,9	1	0
LM_4	117	4,70	1,315	0	,0	0	0
LM_5	117	4,64	1,316	0	,0	9	9
FINSEF_1_R	117	4,04	1,704	0	,0	0	0
FINSEF_2_R	117	4,34	1,492	0	,0	0	0
FINSEF_3_R	117	5,15	1,324	0	,0	0	0
FINSEF_4_R	117	5,31	1,534	0	,0	17	0
FINSEF_5_R	117	5,24	1,535	0	,0	3	0
FINCONC_1_R	117	2,76	1,928	0	,0	0	0
FINCONC_2	117	3,26	1,863	0	,0	0	0
FINCONC_3	117	3,01	1,556	0	,0	0	2
FINCONC_4	116	3,14	2,142	1	,9	0	0
AIAT_1	116	5,01	1,261	1	,9	1	0
AIAT_2_R	116	3,99	1,634	1	,9	0	0
AIAT_3	116	4,75	1,243	1	,9	7	6
AIAT_4_R	116	5,06	1,353	1	,9	1	0
AIU_1	116	4,21	1,442	1	,9	0	0
AIU_2_R	116	4,78	1,455	1	,9	0	0
AIU_3	116	4,62	1,263	1	,9	1	0
Complicated_Control	116	2,40	1,376	1	,9	0	3
PERC_1	116	3,73	1,482	1	,9	0	0
PERC_2	117	4,58	1,275	0	,0	3	0
PERC_3	117	4,27	1,448	0	,0	0	0
PERC_4	117	4,33	1,259	0	,0	15	1
PERC_5	117	4,01	1,447	0	,0	0	0
PERC_6	117	4,51	1,243	0	,0	8	3
PERC_7	117	4,16	1,313	0	,0	0	0
PERC_8	117	4,22	1,226	0	,0	13	2
PERC_9	117	4,15	1,400	0	,0	0	0
HEDV_1_R	117	5,33	1,414	0	,0	16	0
HEDV_2	117	4,43	1,155	0	,0	10	1
HEDV_3	117	3,42	1,139	0	,0	4	4
Duration	117	0:10:45	0:00:53	0	,0	0	0
Dur_sec	117	645,4312	53,42318	0	,0	0	0
Dur_min	117	10,7574	,89059	0	,0	0	0
Tot_fix	117	1475,47	572,449	0	,0	0	0
Fix_per_sec	117	2,2803	,85281	0	,0	0	0
Tot_blinks	117	163,84	95,822	0	,0	0	4
Sec_between_blink	117	5,3851	3,31412	0	,0	0	3
Blink_per_min	117	15,2997	8,95633	0	,0	0	3
Avg_pup_dil	117	2,77094017094	,901559934422	0	,0	0	0
Avg_Fix_dur	117	,5401	,33557	0	,0	0	5
Study	117	2,84	2,515	0	,0	0	0
Personalization_mani	117			0	,0		
filter_$	117			0	,0		
Validdata	117			0	,0		
Valid	117			0	,0		
Behaviour	114			3	2,6		
Personalization	117			0	,0		
Gender	117			0	,0		

a. Number of cases outside the range (Q1 - 1.5*IQR, Q3 + 1.5*IQR).

b. . indicates that the inter-quartile range (IQR) is zero.

Study	.	-,056	,113	,(

a. Little's MCAR test: Chi-Square = 102,889, DF = 93, Sig. = ,227

Appendix 8: SPSS tests experiment

Group Statistics

	Personalization_mani	N	Mean	Std. Deviation	Std. Error Mean
MANI_LM_1	Personalized	58	4,57	1,230	,161
	Non-personalized	59	3,61	1,246	,162
MANI_2_R	Personalized	58	5,22	1,093	,144
	Non-personalized	59	3,59	1,416	,184
MANI_3	Personalized	58	5,86	1,330	,175
	Non-personalized	59	2,83	1,588	,207

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
MANI_LM_1	Equal variances assumed	,166	,685	4,188	115	<,001	<,001	,959	,229	,505	1,412
	Equal variances not assumed			4,189	114,998	<,001	<,001	,959	,229	,505	1,412
MANI_2_R	Equal variances assumed	7,205	,008	6,967	115	<,001	<,001	1,631	,234	1,167	2,095
	Equal variances not assumed			6,982	108,913	<,001	<,001	1,631	,234	1,168	2,094
MANI_3	Equal variances assumed	1,435	,233	11,182	115	<,001	<,001	3,032	,271	2,495	3,569
	Equal variances not assumed			11,199	112,189	<,001	<,001	3,032	,271	2,495	3,568

Group Statistics

	Personalization_mani	N	Mean	Std. Deviation	Std. Error Mean
Personalization_avg	Personalized	58	5,2184	,83666	,10986
	Non-personalized	59	3,3446	1,00757	,13117

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Personalization_avg	Equal variances assumed	,884	,349	10,934	115	<,001	<,001	1,87376	,17137	1,53430	2,21321
	Equal variances not assumed			10,951	111,887	<,001	<,001	1,87376	,17110	1,53474	2,21278

Group Statistics

	Personalization_mani	N	Mean	Std. Deviation	Std. Error Mean
Complicated_Control	Personalized	57	2,16	1,236	,164
	Non-personalized	59	2,63	1,473	,192

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means							
						Significance				95% Confidence Interval of the Difference	
		F	Sig.	t	df	One-Sided p	Two-Sided p	Mean Difference	Std. Error Difference	Lower	Upper
Complicated_Control	Equal variances assumed	4,392	,038	-1,855	114	,033	,066	-,469	,253	-,970	,032
	Equal variances not assumed			-1,861	111,839	,033	,065	-,469	,252	-,969	,030

AI_edu_exp

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Yes	1	,9	,9	,9
	No	115	98,3	98,3	99,1
	Other	1	,9	,9	100,0
	Total	117	100,0	100,0	

Independent Samples Test

		Levene's Test for Equality of Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
cred_average	Equal variances assumed	,352	,554	1,011	115	,314	,17544	,17357	-,16837	,51925
	Equal variances not assumed			1,009	112,003	,315	,17544	,17379	-,16891	,51978

Group Statistics

	Personalization_mani	N	Mean	Std. Deviation	Std. Error Mean
cred_average	Personalized	58	4,3091	1,00577	,13206
	Non-personalized	59	4,1337	,86775	,11297

Appendix 9: Output SmartPLS

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Learning motitvation	0.753	0.811	0.833	0.505
Perceived credibility	0.870	0.917	0.894	0.485

	R-square	R-square adjusted
Avg_pup_dil	0.005	-0.012
Decision to act	0.210	0.159
Learning motitvation	0.267	0.220
Perceived credibility	0.007	-0.002

	Outer loadings
Avg_pup_dil <- Avg_pup_dil	1.000
Complicated_Control <- Complicated_Control	1.000
Dummy_Behavior <- Behavior	1.000
Dummy_PERS <- Personalization	1.000
Dummy_gender <- Male	1.000
LM_2_R <- Learning motitvation	0.635
LM_3 <- Learning motitvation	0.694
LM_4 <- Learning motitvation	0.824
LM_5 <- Learning motitvation	0.529
MANI_LM_1 <- Learning motitvation	0.826
Management_Dummy <- Management_study	1.000
PERC_1 <- Perceived credibility	0.555
PERC_2 <- Perceived credibility	0.616
PERC_3 <- Perceived credibility	0.701
PERC_4 <- Perceived credibility	0.750
PERC_5 <- Perceived credibility	0.661
PERC_6 <- Perceived credibility	0.668
PERC_7 <- Perceived credibility	0.760
PERC_8 <- Perceived credibility	0.728
PERC_9 <- Perceived credibility	0.797
englishskill <- englishskill	1.000

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Learning motitvation	0.753	0.811	0.833	0.505

Perceived credibility	0.870	0.917	0.894	0.485

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
Avg_pup_dil -> Decision to act	0.090	0.089	0.036	2.477	0.013
Avg_pup_dil -> Learning motitvation	0.134	0.138	0.086	1.557	0.119
Complicated_Control -> Decision to act	-0.019	-0.019	0.037	0.519	0.603
Complicated_Control -> Learning motitvation	-0.203	-0.205	0.092	2.198	0.028
Male -> Decision to act	0.271	0.272	0.082	3.319	0.001
Male -> Learning motitvation	0.275	0.290	0.174	1.581	0.114
Management_study -> Behavior	-0.181	-0.177	0.077	2.344	0.019
Management_study -> Learning motitvation	-0.325	-0.321	0.192	1.691	0.091
Perceived credibility -> Avg_pup_dil	0.015	0.020	0.126	0.119	0.905
Perceived credibility -> Behavior	0.023	0.026	0.044	0.531	0.596
Perceived credibility -> Learning motitvation	0.237	0.246	0.120	1.974	0.048
Personalization -> Avg_pup_dil	-0.142	-0.138	0.185	0.765	0.444
Personalization -> Behavior	0.173	0.176	0.082	2.097	0.036
Personalization -> Learning motitvation	0.573	0.589	0.186	3.081	0.002
Personalization -> Perceived credibility	0.165	0.209	0.233	0.708	0.479
englishskill -> Behavior	-0.001	-0.002	0.037	0.031	0.975
englishskill -> Learning motitvation	0.024	0.019	0.096	0.248	0.804

	VIF
Avg_pup_dil	1.000

Complicated_Control	1.000
Dummy_Behavior	1.000
Dummy_PERS	1.000
Dummy_gender	1.000
LM_2_R	1.315
LM_3	1.591
LM_4	2.125
LM_5	1.380
MANI_LM_1	1.604
Management_Dummy	1.000
PERC_1	1.687
PERC_2	1.840
PERC_3	1.915
PERC_4	1.806
PERC_5	1.726
PERC_6	2.419
PERC_7	2.774
PERC_8	2.304
PERC_9	2.608
englishskill	1.000

	R-square	**R-square adjusted**
Avg_pup_dil	0.005	-0.012
Behavior	0.210	0.159
Learning motitvation	0.267	0.220
Perceived credibility	0.007	-0.002

	Total effects
Avg_pup_dil -> Decision to act	0.090
Avg_pup_dil -> Learning motitvation	0.134
Complicated_Control -> Decision to act	-0.019
Complicated_Control -> Learning motitvation	-0.203
Male -> Decision to act	0.271
Male -> Learning motitvation	0.275
Management_study -> Decision to act	-0.181
Management_study -> Learning motitvation	-0.325
Perceived credibility -> Avg_pup_dil	0.015
Perceived credibility -> Decision to act	0.023
Perceived credibility -> Learning motitvation	0.237
Personalization -> Avg_pup_dil	-0.142
Personalization -> Decision to act	0.173
Personalization -> Learning motitvation	0.573
Personalization -> Perceived credibility	0.165
englishskill -> Decision to act	-0.001

englishskill -> Learning motitvation	0.024

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Personalization -> Perceived credibility -> Avg_pup_dil	0.002	0.005	0.041	0.061	0.952
Personalization -> Perceived credibility -> Avg_pup_dil -> Learning motitvation	0.000	0.001	0.008	0.042	0.966
Personalization -> Perceived credibility -> Decision to act	0.004	0.004	0.015	0.247	0.805
Personalization -> Perceived credibility -> Avg_pup_dil -> Decision to act	0.000	0.000	0.004	0.053	0.958
Personalization -> Perceived credibility -> Learning motitvation	0.039	0.037	0.064	0.606	0.545
Perceived credibility -> Avg_pup_dil -> Decision to act	0.001	0.002	0.013	0.106	0.915
Perceived credibility -> Avg_pup_dil -> Learning motitvation	0.002	0.003	0.022	0.093	0.926
Personalization -> Avg_pup_dil -> Decision to act	-0.013	-0.013	0.019	0.672	0.502
Personalization -> Avg_pup_dil -> Learning motitvation	-0.019	-0.019	0.034	0.566	0.571

	Avg_pup_dil	Complicated_Control	Decision to act	Learning motitvation	Male	Management_study	Perceived credibility	Personalization	englishskill
Avg_pup_dil			0.048	0.023					
Complicated_Control			0.002	0.051					
Decision to act									
Learning motitvation									
Male			0.100	0.022					
Management_study			0.048	0.033					
Perceived credibility	0.000		0.003	0.069					
Personalization	0.005		0.047	0.093			0.007		
englishskill			0.000	0.001					

Path coefficients (with significance) β-coefficient

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Avg_pup_dil -> Decision to act	0.090	0.089	0.036	2.477	0.013
Avg_pup_dil -> Learning motitvation	0.134	0.138	0.086	1.557	0.119
Complicated_Control -> Decision to act	-0.019	-0.019	0.037	0.519	0.603
Complicated_Control -> Learning motitvation	-0.203	-0.205	0.092	2.198	0.028
Male -> Decision to act	0.271	0.272	0.082	3.319	0.001
Male -> Learning motitvation	0.275	0.290	0.174	1.581	0.114
Management_study -> Decision to act	-0.181	-0.177	0.077	2.344	0.019
Management_study -> Learning motitvation	-0.325	-0.321	0.192	1.691	0.091

Perceived credibility -> Avg_pup_dil	0.015	0.020	0.126	0.119	0.905
Perceived credibility -> Decision to act	0.022	0.025	0.043	0.504	0.614
Perceived credibility -> Learning motitvation	0.235	0.244	0.123	1.905	0.057
Personalization -> Avg_pup_dil	-0.144	-0.143	0.191	0.757	0.449
Personalization -> Decision to act	0.182	0.184	0.080	2.267	0.023
Personalization -> Learning motitvation	0.554	0.571	0.187	2.961	0.003
Personalization -> Perceived credibility	0.165	0.209	0.233	0.708	0.479
englishskill -> Decision to act	-0.001	-0.002	0.037	0.031	0.975
englishskill -> Learning motitvation	0.024	0.019	0.096	0.248	0.804

Appendix 10: structural and measurement model

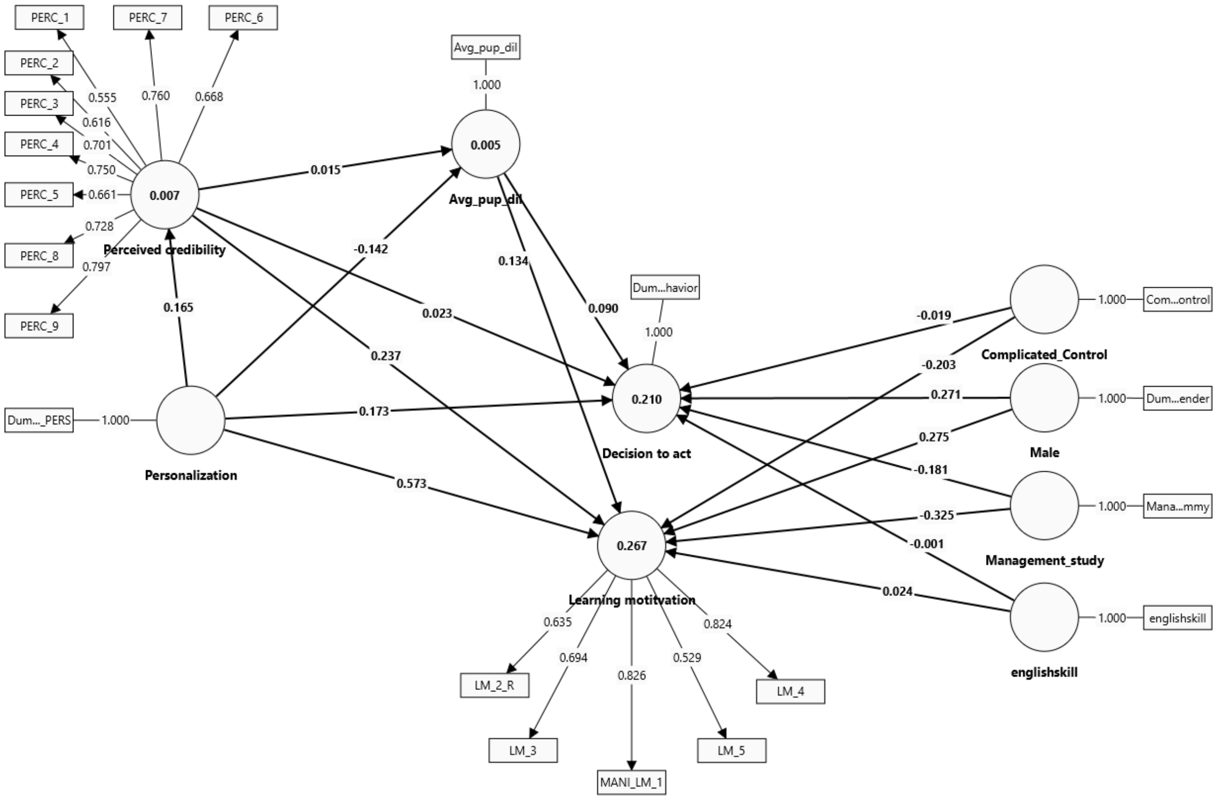

Figure 1:Measurement model

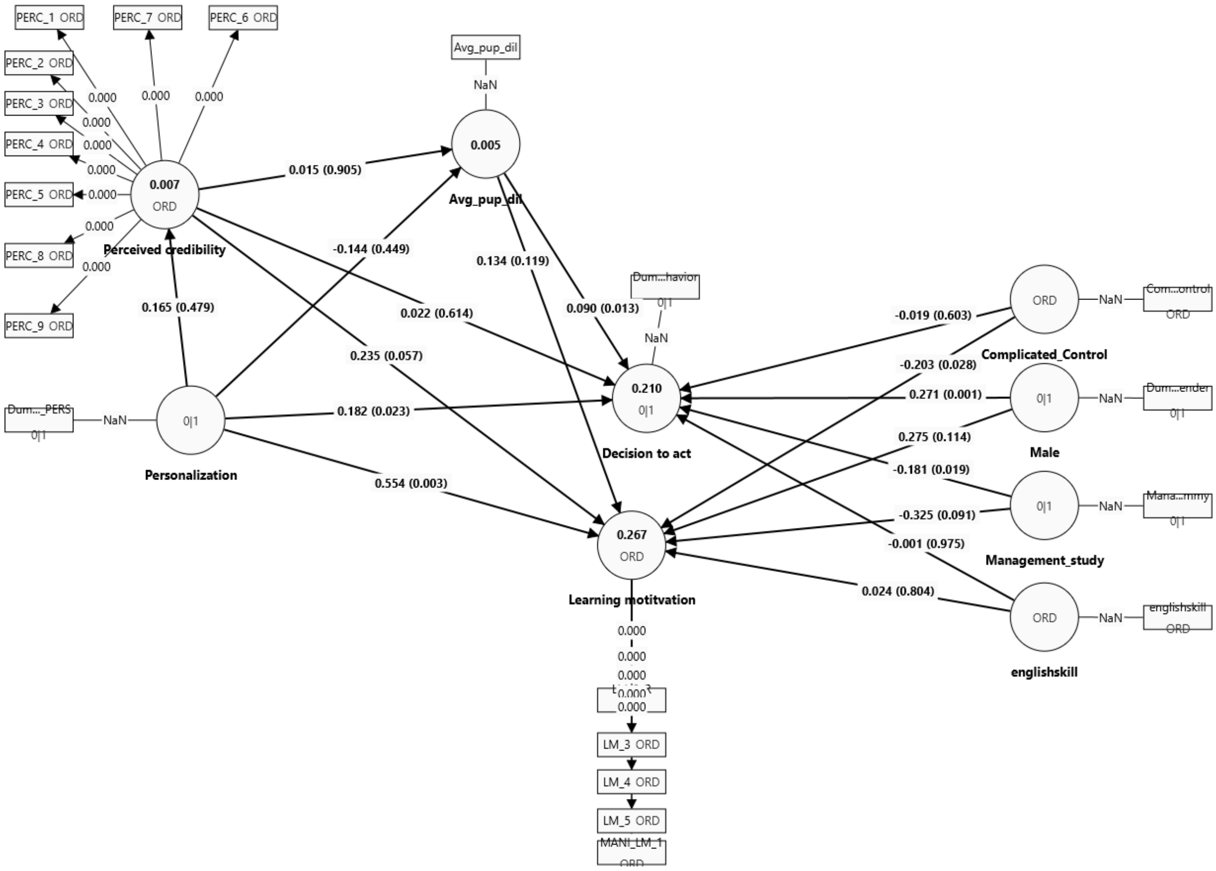

Figure 2: Structural model