Uncovering the potential of Generative-AI in improving financial literacy

Exploring the role of the cognitive and affective dimension of customer experience in the relationship between Generative-AI personalization and taking action to improve financial literacy

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Abstract

The purpose of this study is to explore how the use of personalized GenAI content can encourage students to improve their financial literacy, taking into account hedonic value and cognitive load of the affective and cognitive dimensions of customer experience, respectively, and moderated by attitude towards AI. This research uses a 2x1 between subjects experimental design with personalization being manipulated. During an educational experience with an eye tracker, 117 participants were exposed to a GenAI financial tutor, after which they answered multiple scale questions. Structural Equation Modelling was used to analyse the measurement and structural model and examine the hypothesized effects. Findings demonstrate a positive effect of GenAI-personalization on action taking to improve financial literacy, however not mediated by hedonic value or cognitive load, or moderated by attitude towards AI. Additionally, there was a marginally significant effect of hedonic value on action taking to improve financial literacy. This research contributes to existing literature by measuring the effect of personalized GenAI in educational settings, therefore deepening the understanding of this concept in both the educational and the customer experience field. For firms, this managers, this research helps understanding the effect of personalized educational content on certain aspects of the customer experience and eventually on financial literacy improving behaviour. Concluding, this research contributes to a more nuanced understanding of how personalized GenAI can be utilized to enhance educational outcomes and improve financial literacy.

Keywords: *GenAI, eye-tracking, personalization, financial literacy, customer experience, hedonic value, cognitive load, attitude towards AI*

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1. Introduction

During the last years, college students are increasingly more stressed-out about their finances than before. Out of a sample of 4,488 US college students, 71,4% reported being stressed about their financial situation (Heckman et al., 2014). Experiencing financial stress can have major negative effects on college students. Financial stress leads to approximately one-third of college students neglecting their academic work and even leads to one-fourth of college students considering dropping out of college (Montalto et al., 2019). Understanding financial situations and the behaviours that result from those, including making use of student loans and credit cards, is a vital element of financial wellness (Montalto et al., 2019). While using credit cards and borrowing money from institutions is becoming more readily available, only half of adults in emerging nations making use of these financial utilities is actually financially literate (Klapper & Lusardi, 2019). In addition, the same research found only one-third of all adults worldwide to be financially literate. Researchers define financial literacy as: ‘’The ability to use knowledge and skills to manage financial resources effectively for a lifetime of financial well-being.’’ (Hung et al., 2009, p. 5; PACFL, 2008). In order to increase financial literacy, financial education in high school and in college could be a valuable incentive (Montalto et al., 2019).

Practical Need

As financial stress levels are rising under college students (Heckman et al., 2014), the likelihood of students considering dropping out or reducing his/her coursework (Joo et al., 2008), and having poor physical and mental health (Roberts et al., 2000) increases. In a study with 4,488 students from 19 different American colleges across the state of Ohio, 71.4% of the students reported feeling financial stress from personal finances (Heckman et al., 2014). In addition, a 2023 survey answered by 1,786 UK students showed that 67% of students were stressed about paying back their loan and 82% were stressed about having sufficient money to make ends meet (Brown, 2023). A possibility to reduce financial stress levels lays in increasing student’s financial self-efficacy. Financial self-efficacy is defined as: ‘’One’s sense of being prepared and able to handle financial responsibility’’ (Montalto et al., 2018, p. 15). Students with high financial self-efficacy experience less financial stress than students with low financial self-efficacy (Heckman et al., 2014). Since a decrease in financial stress also leads to a decrease in students considering dropping out of college (Joo et al., 2008) and better physical and mental health (Roberts et al., 2000), it becomes clear that educating students on financial literacy has multiple beneficial effects. A study containing 409 university students across eight different European countries, found that in all eight countries, students on average reported financial literacy levels ranging between 65.3% and 77.3%, all classified as a medium score (Ergün, 2018). Furthermore, a study conducted on a sample of 1,493 American college students, found the average financial literacy level to be 43.05%, which is even lower than their European counterparts (Brau et al., 2019). This indicates that there is enough room for improving financial literacy among students.

Besides that financial education programs are very costly to develop and implement (Willis, 2011), students' motivation to learn about financial literacy also affects the effectiveness of financial education on students' financial behaviour (McCormick, 2009). College students are more motivated to learn about financial literacy in one-on-one peer sessions than in traditional classroom sessions, since they prefer the informal setting and may feel uncomfortable asking questions in class (Maurer & Lee, 2011). However, many financial education programs utilize a ''one size fits all" approach, which are not suitably designed for its target population and potentially waste significant resources such as time, money and effort (Maurer & Lee, 2011). In order to be effective, financial education would need to be in an intensive and frequent one-on-one setting, with personalized content for the consumer (Willis, 2011). However, implementing this approach would be so costly, since it requires highly skilled and thus expensive financial educators, that the financial knowledge benefits obtained by the individuals during the course would in the end not outweigh the purchasing costs of the program (Willis, 2011). Thus, other ways of financially educating students have to be examined. Since a lack of financial knowledge also leads to poor financial decision-making and debt accumulation (Lusardi & Mitchell, 2014), it is crucial to find effective ways of motivating college students to financially educate themselves.

In summary, the studies mentioned above show that in order to reduce financial stress under college students, the financial literacy level of those students has to be improved. However, the problem is that with current financial education programs, students are not motivated enough to become more financially literate. Extant research on these financial education programs, however, offers little guidance.

Theoretical Need

Existing research on improving financial literacy mainly focuses on traditional education programs. Studies focusing on traditional financial education programs have shown that classroom-based financial education has limited effectiveness in improving financial literacy (Mandell & Klein, 2009; Carpena et al., 2019). While the addition of personalized counselling to these programs could positively affect financial literacy, costs remain very high (Carpena et al., 2019; Willis, 2011). Few studies however, examine the effectiveness of offering and targeting financial education to specific groups in other ways (Lusardi, 2019).

Gligorea et al. (2023) provide a literature review, covering the integration of artificial intelligence (AI) and machine learning (ML) in adaptive e-learning. The authors conclude that integrating AI and ML in e-learning can, by using data-driven personalization, enhance student engagement and improve overall learning outcomes. However, no study yet researched the effect of generative AI-personalization in financial education. Polk et al. (2020) describes personalization as a process designed to generate an individualized and relevant interaction to enhance customer experience. The concept of customer experience is becoming an increasingly relevant topic in research. Ensuring a positive customer experience for consumers is essential for firms to increase satisfaction, loyalty and competitive advantage (Jain et al., 2017). Therefore, researching and evaluating customer experience can be of crucial value for firms. Customer experience is described as follows; ''Customer experience encompasses every aspect of a company's offering—the quality of customer care, of course, but also advertising, packaging, product and service features, ease of use, and reliability. It is the internal and subjective response customers have to any direct or indirect contact with a company" (Meyer and Schwager, 2007, pp. 1-2). Customer experience is a combination of cognitive, emotional, physical, sensorial and social elements (De Keyser et al., 2015). The cognitive dimension contains all mental processes; the emotional, also called affective, dimension covers the affect, mood and feelings; the physical (behavioural) dimension involves physical actions; the sensorial dimension relates to the senses; the social dimension involves social relationships (Gentil et al., 2007; Keiningham et al., 2017; Brun et al., 2017). On the one hand, Sidaoui et al. (2020) dives deeper into the affective dimension, dividing it into emotion, mood and hedonic value. Hedonic value can be explained as the sensory stimulation and pleasure that people encounter in the buying process (Holbrook & Hirschman, 1982). Sidaoui et al. (2020) argue that these three terms represent a more experience-specific embodiment of affect. In addition, it is essential to capture all three sub-elements simultaneously to gain a holistic understanding of the experiental feelings that emerge during the customer experience (Kranzbühler et al., 2018). On the other hand, Costley & Lange (2017) dive deeper into the cognitive dimension, researching the effect of personalization on cognitive load, the process of transferring information from working memory to long-term memory (Sweller et al., 2019)

Various studies call for future research into the effects of personalization on cognitive load (Lim & Benbasat, 2000; Lange, 2023), hedonic experiences (Lim & Benbasat, 2000; Desai, 2020), and behaviour (De Keyzer et al., 2015; Costley & Lange, 2017). Consequently, prior research highlights the need for future research into the influence hedonic value (Kazakeviciute & Banyte, 2012) and cognitive load (Costley & Lange, 2017; Vyvey et al., 2018) have on behaviour. In summary, both a theoretical and managerial need exists for further research on how a Gen-AI service experience could provide new insights for the fields of both customer experience and financial literacy improvement.

Research Objective

To address these needs, the following research question has been formulated: ''What is the role of *cognitive load* and *hedonic value*, of respectively the cognitive and affective dimensions of customer experience, in the relationship between *Generative-AI personalization* and *taking action to improve financial literacy*, and how does *attitude towards AI* influence this relationship?". By researching this, the before-mentioned research gaps are addressed by focusing on (a) exploring the effects of GenAI as an effective alternative for traditional ways of improving financial literacy, and (b) examining the relationship between personalized GenAI content and *hedonic value* along with *cognitive load*, as well as (c) the effect of *hedonic value* and *cognitive load* on financial literacy improving behaviour. The purpose of this study is to explore the effectiveness of GenAI in improving financial literacy. However, the last few years, AI has taken an increasingly prominent role in society. It is being used for translating, chatbots, personalized marketing and to carry out other jobs for humans. Nevertheless, the rise of AI-technologies is not always looked upon positively (Stein et al., 2024). Some argue that AI could lead to the downsizing of human jobs (Ivanov et al., 2020), or an increasing lack of control over these rapidly developing technologies (Fast & Horvitz, 2016). The recent presentation of GenAI, such as ChatGPT, has raised concerns about academic fraud, artistic license and the value of human creativity (Thorp, 2023). Individuals may differ enormously in their evaluation of the possibilities and risks AI provides, resulting in many different attitudes toward AI (Stein et al., 2024). Especially since this current research uses personalized GenAI content as a manipulation in the experiment, participant's *attitude towards AI* may influence the research results severely. Therefore, *attitude towards AI* is used to moderate the relationship between *GenAI-personalization* and the behavioural outcome variable, mediated by the cognitive and affective dimensions.

Scientific & Societal Relevance

Including a lab experiment and eye-tracking technology, this study researches the domain of Generative-AI (*GenAI*) *personalization* and *attitude towards AI*, examining their influence on *cognitive load* (representing the cognitive CE dimension) and *hedonic value* (representing the affective CE dimension) within the context of *taking action to improve financial literacy*. This study makes an important contribution to the Gen-AI and education literature, since it sheds a light on how and to what intensity *GenAI-personalization* could be used to educate and motivate students to educate themselves even more on financial literacy. Where other research argues that personalized traditional financial education content does not effectively improve financial literacy (Mandell & Klein, 2009; Carpena et al., 2019), this research intents to uncover effective ways of motivating students to improve their financial literacy by examining personalized GenAI as a replacement for the use of expensive financial experts in education. Besides, by assessing how *GenAI-personalization* influences both cognitive and affective processes, this study offers a comprehensive understanding of the underlying mechanisms of consumer behaviour in context of financial literacy and education.

The results of the research provide insights for managers into the effects of different degrees of personalization on the customer experience and eventual behaviour. Understanding the importance of the *hedonic value* as consumer experiences as a reaction to personalization, could help managers design more effective advertisements. For example, if the results provide evidence for people experiencing low *hedonic value* to be less likely to act after personalization, managers could think of including hedonic elements to their advertisement to encourage positive associations with the company. In addition, examining the moderating effect of *attitude towards AI* on the relationship between *Gen-AI personalization* and customer experience could assist managers in exploring whether there is a need to implement strategies to positively affect *attitude towards AI* and enhance customer experience.

Outline

The outline of the remaining part of this study is as follows. First, the theoretical background of the conceptual model, with corresponding hypotheses, is discussed. Secondly, the methodology of the study is explained. Third, the results of the study are demonstrated. Fourth, the conclusion and discussion are discussed, followed by the practical and theoretical implications, limitations, and recommendations for future research.

2. Theoretical Background

Delving into the theoretical landscape of *Gen-AI personalization* and its impact on *taking action to improve financial literacy*, mediated by the cognitive and affective customer experience dimensions, this section aims to explain the core concepts of this study more in depth. First, the potential for Gen-AI in education is described, before elaborating in-depth on customer experience in general and unfolding the cognitive and affective dimensions.

2.1 Generative Artificial Intelligence in Education

Gen-AI is a technology that uses techniques such as machine learning and neural networks to generate new content by analysing information and patterns from training data (Ooi et al., 2023). Neural networks are computational models that consist of interconnected nodes that process information, also named neurons (Gurney, 2018). The concept of machine learning can be explained as a branch of computing science that focuses on enabling computers to learn without being programmed (Bi et al., 2019). Because of the use of the learning models Gen-AI utilizes, the technology has the capability to comprehend and reproduce human languages, synthesize data, and construct nuanced and structured responses to asked questions (Ooi et al., 2023). In the study of Ooi et al. (2023), the authors state that these capabilities, combined with the pattern recognition Gen-AI utilizes, enables the technology to produce original information. Therefore, it can be used for text summarization, language translation and direct dialogues with humans. Other research supports the promising potential of Gen-AI in education, as it can deliver personalized learning experiences and enhanced interactivity, thereby maximizing both teaching and learning (Baidoo-Anu et al., 2023; Holmes et al., 2023). Moreover, students show a willingness to use Gen-AI in education, especially when factors such as perceived ease of use and perceived trust in the AI are high (Jain & Raghuram, 2024).

2.2 Customer Experience

In order to motivate students to improve their financial literacy, it is important to understand that the educational experience is part of the overall customer experience (Mononen et al., 2016). Various researchers (Schmitt, 1999; Verhoef et al., 2009; Brakus et al., 2009) agree that customer experience can be separated into five types of experience dimensions: sensorial, emotional, cognitive, behavioural and social. First of all, the sensorial dimension refers to the perception of experience through one, or a combination, of the five senses: sight, touch, sound, taste and smell (Schmitt, 1999). Secondly, the emotional or affective dimension appeals to the affective system through the generation of feelings, emotions and moods. This experience focuses mainly on creating an affective relationship between consumers and a company, brand or product (Gentil et al., 2007). Third, the cognitive dimension consists of conscious mental processes. These exist of memory, perception, problem-solving, abstract thinking and language processes (Keiningham et al., 2017). Fourth, the behavioural dimension refers to experiences that affect the consumer in a physical manner. This involves experiences that are so convincing that they result in changing habits or influencing a person to take certain actions (Brun 2017). Fifth, the social dimension contains the individual person itself and the relationships that person has with others. This experience results from relating to a certain group or culture and therefore having the desire to use the same products or services as that group (Gentil et al., 2007).

Taking into account these dimensions, De Keyser et al. (2015, p. 4) describes customer experience as: ‘’The cognitive, emotional, physical, sensorial, and social elements that mark the customer’s direct or indirect interaction with a [set of] market actor[s].’’. De Keyser et al. (2020), labels those interactions as touchpoints. The firm-consumer interaction has a large amount of touchpoints, such as website browsing, in-store visits, or social media interactions. Depending on the context, the circumstances around each touchpoint, and the quality of the touchpoint, such as degree of personalization and service quality, the customer experience is affected differently. Nowadays, more and more of the online touchpoints are interactions with Gen-AI, such as chatbots in customer service for example. Therefore, Gen-AI starts to play an increasing role in shaping customer experience. Especially in the first few years of implementing AI, this could be a challenge for firms, since a high AI-service quality has a positive effect on customers identifying with the brand (Nguyen et al., 2022). However, Lemon and Verhoef (2016) emphasize that customer experience is not limited to product or service usage, but that it also encompasses emotional factors such as satisfaction and loyalty. Therefore, Lemon and Verhoef view customer experience as a holistic concept, containing interrelated tangible and intangible factors that lead to a subjective response, such as an affective response.

2.3 The Affective Dimension

The affective dimension of customer experience relates to the generation of emotions, mood and *hedonic value* during experiences of consumption (Sidaoui et al., 2020). These can be described more precisely by their features, like intensity, duration, cause, awareness and control (Scherer, 2005). The affective aspects have a significant effect on the preferences, evaluations, recommendations and purchase intentions of consumers (Westbrook, 1987). An affective experience, both positive and negative, has an impact on a consumer’s memory by creating long-term associations resulting in a meaningful experience (Pine & Gilmore, 1998). However, affective experiences are evaluated subjectively. In other words, different people can experience different affective reactions to the same action under the same circumstances (Kuuru et al., 2020). According to Carlson et al. (2007), emotions play a crucial role in the determination of behaviour and actions. These emotions are paired with physiological processes and physical actions, such as gestures, posture and facial features. Since these emotions are experienced subjectively, these physical actions also manifest differently per person (Kuuru et al., 2020). In summary, the subjective nature of these affective processes emphasize the complexity and individuality of consumer emotional responses. This contrasts with the cognitive dimension, which involves more objective mental processes.

2.4 The Cognitive Dimension

As already mentioned before, the cognitive dimension of customer experience consists of the mental processes that a consumer experiences, such as perception, memory language, problem solving and abstract thinking (Keiningham et al., 2017). In the paper of Keiningham et al., the authors delineate two main perspectives of the cognitive dimension: the goal attainment perspective and the (dis)confirmation of expectations perspective. On the one hand, the goal attainment perspective follows the assumption that consumers engage in consumption activities to achieve a specific goal (Bagozzi & Dholakia, 1999). For example, students go to college to enhance their knowledge, or buy summaries to help them obtaining a higher grade. These goals are set either consciously or unconsciously. According to this perspective, consumers evaluate their customer experience depending on how effectively they achieved these goals. On the other hand, the (dis)confirmation of expectations perspective follows the assumption that before choosing a service, consumers have expectations. Whether those expectations are confirmed or not, is determined by analysing the level of customer satisfaction (Gentil et al., 2007; Homburg et al., 2006). Early literature labelled this evaluation as mainly cognitively driven (Oliver, 1980; Bitner, 1990), but more recent research shows that the matter is influenced by both cognitive and affective processes (Wirtz & Bateson, 1999). According to Wirtz and Bateson, this is since customer experience expectations are shaped by a combination of objective (cognitive) attributes, such as past experiences and knowledge, and subjective (affective) perceptions, such as emotions, mood and feelings. For example, the expectation of restaurant customers may not only be influenced by the quality of food, but also by the anticipation of the atmosphere in the restaurant or the feeling of being treated politely by the staff. An element of the cognitive dimension is *cognitive load*: the mental effort that consumers require to process information and perform tasks during the interaction (Sweller, 2011). *Cognitive load* can be divided into three types: intrinsic load, extraneous load and germane load (Sweller, 2010). Intrinsic load is concerned with the intrinsic complexity of received information, extraneous load is concerned with the design of the instruction and germane load is concerned with the acquisition of knowledge. Of those three types, germane and extraneous load are related to learning processes (Leppink et al., 2013), and are thus the most involved types of load in an educational context.

2.5 Hypotheses development

The relationships between *Generative AI-personalization* and *cognitive load*, *hedonic value*, *attitude towards AI*, and *action taken to improve financial literacy* are shown in *Figure 1* below, including the hypotheses. In the conceptual model, the affective customer dimension is represented by the concept of *hedonic value*. The cognitive dimension is represented by *cognitive load*, one of the elements of this dimension. Since in the experiment, behaviour is measured by tracking whether participants took a flyer with financial educational content, the behavioural outcome variable is represented by ‘ *’action* *taken to improve financial literacy*". The following sections present the hypothesis, which will be discussed in numerical order.

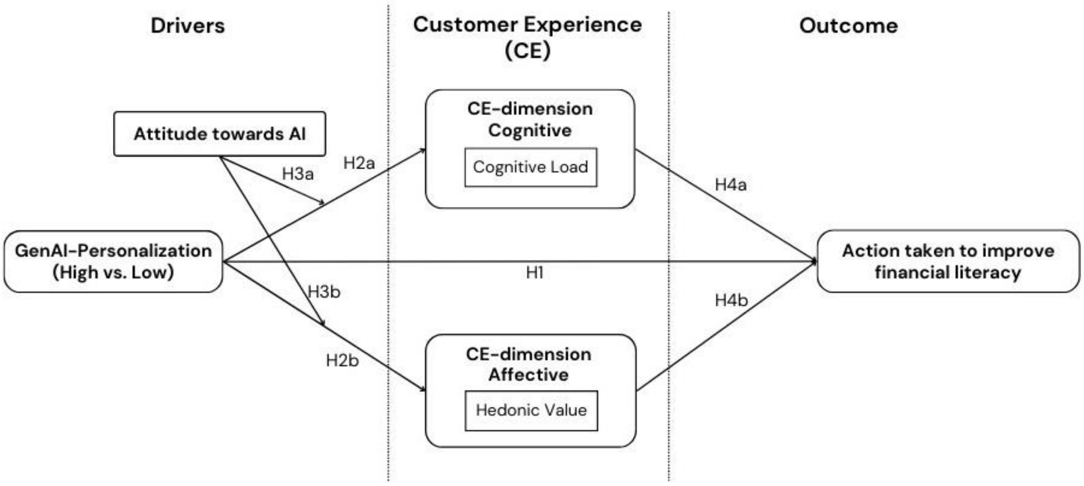

Figure 1

A study by Cordova and Lepper (1996), who examined the effect of contextualization, personalization and provision of choice strategies on the learning process, found that personalized learning contexts resulted in higher motivation to learn. Moreover, a study researching the impact of personalized learning on motivation in online higher education concluded that personalized learning content increases learning engagement and thus motivation to learn (Alamri et al., 2020). In addition, Tokan and Imakulata (2019) provided evidence for intrinsic learning motivation to directly affect learning behaviour and learning achievement, meaning that motivation results in actual behaviour. Therefore, the following hypothesis is formulated:

H1: GenAI-Personalization has a positive direct effect on action taken to improve financial literacy

Since this paper researches a relatively undiscovered subject, some of the hypothesis are based on studies researching personalization or customer experience outside of educational contexts. In another context, research covering personalized learning devices in a museum setting found that personalized learning content reduced intrinsic and extraneous cognitive loads and increased germane cognitive loads (Sun & Yu, 2019). In other words, the complexity of the load decreased and the acquisition of knowledge increases. Since overall, two out of three cognitive load elements decreased, the overall *cognitive load* decreases. This is supported by Zhong (2022), who researched the effect of personalized learning on *cognitive load* in an educational role-playing game environment. Considering these findings, the following hypothesis is formulated:

H2a: GenAI-Personalization has a negative effect on cognitive load

The relationship between the affective dimension of customer experience and personalization of web stores has been examined by Rose et al. (2012). The authors found evidence for personalized content positively affecting customer's emotional state. In a slightly different context, research by Tyrväinen et al. (2020), who researched the effects of personalization in an omnichannel retail setting, confirmed this positive relationship between personalization and the affective dimension. In terms of this affective dimension, Nikolaev (2018) examined the relationship between higher education and the *hedonic value* happiness. The results showed that a higher level of education has a positive effect on the *hedonic value*. *Hedonic value*, the sensory stimulation and pleasure that people normally encounter in the buying process (Holbrook & Hirschman, 1982), is an element of the affective customer experience dimension (Sidaoui et al., 2020). Regarding the positive effect personalization has on the affective dimension of customer experience and thus also on *hedonic value*, the following hypothesis is formulated:

H2b: GenAI-Personalization has a positive effect on hedonic value

Building on the evidence of Rose et al. (2012) and Tyrväinen et al. (2020), attitudes towards technology have been shown to influence the effectiveness of technology in achieving preferred outcomes, where positive attitudes facilitate and negative attitudes hinder this effectiveness (Kim & Kankanhalli, 2009). In the context of *GenAI-personalization* in education, this technology refers to the personalization technology. Together with the findings of Sun & Yu (2019), this suggests that a negative *attitude towards AI* leads to an increase in *cognitive load*, while a positive *attitude towards AI* leads to a decrease of *cognitive load*. Therefore, the following hypothesis is formulated:

H3a: Customer's attitude towards AI moderates the relationship between GenAI-Personalization and cognitive load such that (a) the effect is strengthened for positive attitudes against AI and (b) the effect is weakened for negative attitudes towards AI

Furthermore, research shows that when hedonic aspects are prioritized, users may resist AI-recommendation sources. (Longoni & Cian, 2022). Moreover, in a study examining the relation between service value seeking and *attitudes towards AI*, the authors suggested that in contexts where *hedonic values* are more prominent, there might be a greater resistance towards AI (Chi et al., 2022). Consequently, the following hypothesis is formulated.

H3b: Customer's attitude towards AI moderates the relationship between GenAI-Personalization and hedonic value such that (a) the effect is strengthened for positive attitudes against AI and (b) the effect is weakened for negative attitudes towards AI

Furthermore, a study by Hughes et al. (2018) researched the effects of self-regulated learning and *cognitive load* on students completing online video lectures. According to the authors, the results provide evidence for high levels of *cognitive load* to be negatively affecting students' likelihood to fully engage in study tasks. Furthermore, Schunk et al. (2008) argue that motivation to engage in learning activities will diminish as a result of having to persist in following complex or confusing content. This is since *cognitive load* has a negative effect on attention (Hartley, 1999). In other words, a high *cognitive load* leads to lower attention and learning motivation. Therefore, the next hypothesis is formulated:

H4a: Cognitive load has a negative effect on Action taken to improve financial literacy

In terms of the affective dimension of customer experience in purchasing environmental friendly products, Ekawati et al. (2021) examined the effect of *hedonic value*, brand personality appeal and attitude on behavioural intention. The results demonstrated a positive effect of *hedonic value* on behavioural intention. In addition, Desai (2019) found that positive hedonic experience is positively related with behavioural intention as well. Since behaviour is positively affected by *hedonic value*, the following hypothesis is proposed:

H4b: Hedonic value has a positive effect on action taken to improve financial literacy

3. Methodology

The conceptual model depicted in Figure 1 is examined by doing a quantitative lab experiment in an AI-avatar context. The experimental set up allows researchers to deepen the understanding of how individuals experience personalization when interacting with a Gen-AI avatar in an educative context.

3.1 Design

In this research, a Wizard of Oz approach is used. The Wizard of Oz approach refers to a research method where the interactivity in a human-robot interaction, which normally would be controlled by computer technology, is mimicked by the researcher (Weiss et al., 2009. In this research, participants think that they are having an interaction with a generative AI-avatar, while this avatar is in fact controlled by the researchers. During the experiment, other researchers are secretly in a Microsoft Teams call with a laptop in the experiment room, which enables them to listen to everything that is said in the experiment room. This method is chosen, because it allows for realistic interaction without needing a fully developed AI system. The Wizard of Oz approach is considered to be a mainstream method in Human-Computer Interaction research (Weiss et al., 2009) and is thus also used in this research. The experiment makes use of a 2 (*Gen-AI Personalization*: yes vs. no) x 1 between-subjects experimental design. One factor is manipulated: *Gen-AI Personalization*. Altogether, there are two conditions to which the participants can be assigned. All participants are randomly assigned to one of these two conditions. In the first condition, participants face a scenario with no *GenAI-personalization*. The second condition exposes participants to a scenario with *Gen-AI personalization*. The script of the personalized scenario is based on the outputs of an elaborate prompt for an AI tutor optimized for ChatGPT 4 (ChatGPT, 2023) that has been adapted from Mollick and Mollick (2023) (see Appendix 3). For this experiment, the prompt is altered and fits the operationalization of personalization as it tailors to the interests of individual learners. A non-personalized prompt was also created, here all personalization principles were removed (Alamri et al., 2020) (see Appendix 4). The scripts generated by GPT-4 (ChatGPT, 2023) were uploaded to Vidnoz, an AI video text-to-video generator (Vidnoz, n.d.). The videos for shown via playlists from VLC Media Player (VideoLAN, 2023). The topics for each script were determined based on a survey we held for 43 students who ranked financial literacy topics on relevance to them (Appendix 2). The personalized scripts were based on the most relevant themes within three major topics of financial literacy (loans, investing and budgeting), the non-personalized scripts were based on the least relevant themes within these topics. The first pre-test aimed to determine whether the personalized and non-personalized conditions were significantly different but failed to show a significant difference (sig = .351). Research indicates that perceived personalization, rather than actual personalization, drives the effectiveness of personalized messages (Li, 2016, 2019). Participants might not have perceived the differences between the personalized and non-personalized AI avatars as intended. If participants did not clearly perceive one condition as more personalized than the other, their responses would naturally be more similar, leading to a non-significant pre-test result. Therefore, we opted to make the non-personalized script based on the least relevant financial literacy topic to students overall according to the survey (retirements) in order to limit to chances of perceived personalization. The following pre-test showed significant difference between the two conditions (moreover in Chapter 4).

Moving on, the participants are randomly assigned to either the personalized or the non-personalized group. In order to check whether the personalization is manipulated properly, a pre-test and manipulation check of the experiment are done. Participants are not informed about the goal of the experiment. This is to make sure the participant is convinced that he/she is interacting with a computer programmed AI-avatar, instead of a human controlling the avatar.

Manipulation Scenario

In the experiment, participants are informed that they are going to have an interaction with a Generative AI-avatar. Generative-AI refers to computer techniques that have the capability of generating content such as text, images and audio, but also have the capability to assist humans as intelligent question-answering systems (Feuerriegel et al., 2024). During the interaction the participant has, the avatar provides educational content about financial literacy. After an introductory message, the participant is asked which out of three subjects he/she found most interesting. The participant is told to verbally communicate the subject of interest. In the personalized condition, the AI-avatar provides the participant with educational content about the topic of choice. In the non-personalized condition, the participant receives content a totally different and not requested topic: retirements.

3.2 Measurement

In this experiment, one factor is manipulated: *GenAI-personalization*. For that reason, no measures are needed for that construct. Other constructs, such as *cognitive load*, *hedonic value*, *attitude towards AI* and *action taken to improve financial literacy* are measured by existing scales from literature. All constructs and their corresponding measures can be found in Appendix 1

3.2.1 Measurement of Cognitive Load

The first construct to be measured is *cognitive load*. *Cognitive load* can be measured by multiple eye-tracking measures (Meißner & Oll, 2019). Eye-tracking allows researchers to record a participant's eye movement during behavioural processes. Most modern eye-tracking systems use *pupil center corneal reflection* (PCCR), a technique using near-infrared illumination to create reflection patterns on the cornea and pupil of the user's eyes. Then, image sensors of the eye-tracking system make images of the eyes and reflection patterns of the near-infrared light, allowing the system's software to estimate the position of the eye and the point of gaze on the visual stimulus (Cullipher & VandenPlas, 2018). The most frequently used eye-tracking measures in research are: fixation position, fixation rate, fixation duration, saccade distance (=the distance the eyes have travelled between two consecutive fixations) and pupil diameter (Meißner & Oll, 2019). In this research, since participant are eye-tracked during an interaction, using fixation rate measures is most appropriate to evaluate cognitive load (Zagermann et al., 2016). The eye-tracking device has the ability to register the location and timing of eye-movements and fixations (Reichenberger et al., 2020). A fixation occurs when the participant maintains his or her vision on one specific point on the screen (Salminen et al., 2018). In this research, all fixations during the experiment are measured, ignoring differences between certain areas of interest. Furthermore, the fixation rate data will be analysed using the methods proposed by Zagermann et al. (2016). To specify, this method poses that a higher fixation rate will indicate a lower *cognitive load*, while a lower fixation rate will indicate a higher *cognitive load*. This is since a lower fixation rate is an indicator of attention, meaning that the participant is focused (Chen et al., 2011).

Eye-tracking equipment

The eye-tracker that is used in this experiment is the Pupil Core. The Pupil Core is a wearable eye-tracker that can measure up to 200 Hz per eye and 120 Hz per eye in case of a higher resolution (Faraji et al., 2022). Since the Pupil Core is wearable, the participant can freely move his head around and is thus not forced to watch the screen. The eye-tracker has three cameras. The first camera is a world camera, with a fisheye field view. This camera enables researchers to see from the participant's point of view. The other two cameras are individually focussing on either the right or the left eye of the participant, so that both eyes are tracked. The combination of these cameras makes eye-tracking on a wide screen possible (Faraji et al., 2022). The Pupil Core eye-tracker comes provides its own software, called Pupil Player. This software enables the identification of Areas of Interest, which are the places where people look towards, and the analysis of fixations and fixation durations (Pupil Labs, 2023). Fixations are analysed within a time range of 100ms to 400ms, as this is suggested by Salvucci and Goldberg (2000) to be an appropriate duration.

3.2.2 Measurement of Other Constructs

Hedonic value, as an aspect of the affective dimension, is measured by a three-item, seven-point Likert scale, adapted from Batra and Ahtola (1991). Then, the moderator variable, *attitude towards AI*, is measured with a four-item, seven-point Likert scale, adapted from Stein et al. (2024). Finally, the outcome variable, *action taken to improve financial literacy*, is measured using a behavioural measure right after the experiment. After finishing the interaction with the AI-avatar, the participant has the opportunity to either take or not take a flyer containing financial educational content, which is the behavioural measure of the experiment. The outcome of this choice is analysed. As control variables, the variables *age*, *gender*, *faculty of study* and *English language proficiency* are included.

3.3 Procedure

As already described, this experiment uses a Wizard of Oz experimental approach. Before entering the experiment room and starting the experiment, the participant receives a consent form (Appendix 5). With signing the form, the participant gives the researchers permission to use the participant's data obtained during the experiment. Then, without informing the participant, the participants are randomly assigned to one of the two conditions by an automatic randomizing program. Before entering the room, the participant is asked to fill in a questionnaire on a laptop that the researcher provides. After finishing the questionnaire, the participant is allowed to enter the experiment room and take place on a chair in front of a screen. When entering, the participant is asked to put his/her phone on silent mode. Next, the participant is given instructions on the experiment. The participant is told that he/she is going to have a financial educational interaction with an AI-avatar, called Mula. Besides, the researcher informs the participant that he/she receives an eye-tracker, the Pupil Labs Core. The participant is informed that he/she can put on the eye-tracker by himself/herself and that the eye-tracker does not hinder the experiment experience. When the instruction is finished, the participant receives the eye-tracker. After putting it on, the eye-tracker is calibrated using a connected laptop, adjusting the camera positions if necessary. In order to calibrate the eye-tracker properly, the researcher tells the participant to only move the eyes during the calibration, minimize head movements and keep the eyes as wide open as possible. After finishing the calibration, the researcher runs a check to confirm whether the calibration is successful or not. After the check, the participant is instructed to not touch the eye-tracker during the experiment and to remain seated until the end of the experiment. In addition, the researcher wishes the participant good luck and closes the door, which is a sign for the other researchers, secretly listening through a Microsoft Teams call, to start the AI-interaction. From that moment on, the eye-tracking data is collected. During the interaction, the participant verbally answers 7-point scale questions. When the participant is expected to answer, a ''currently listening'' screen is displayed. If during the interaction, the participants response is unclear, the AI will prompt with ''Sorry, I couldn't hear you, could you please repeat yourself?''. At the time the interaction ends, the researcher enters the room again to remove the eye-tracker from the participant's head. Then, the participant is asked to fill in another questionnaire on a laptop provided by the researcher. After the questionnaire, the AI-avatar thanks the participant for participating and tells that if he/she is interested, it is possible to take a flyer with financial educational content on the way out. The flyers, lying on a table next to the door, are faced downwards with the name of the subject (investing, budgeting, or loans) and the text ''please read outside'' written on the back. This is done to prevent participants from reading the flyer inside the experiment room and thus deciding not to take it. When the participant leaves the room, the researcher notes whether or not a flyer was taken.

3.4 Data Analysis Procedure

To analyse the data from the lab experiment, the main data analysis software program that will be utilized is IBM SPSS Statistics, Version 29 (IBM Corp, 2021) and SmartPLS (Ringle, 2022). SmartPLS software can be used to conduct variance-based structural equation modelling using the Partial Least Squares (PLS) method. Structural equation modelling involves testing two distinct models: the measurement model and the structural model. Moreover, with PLS, relationships can be examined simultaneously, making this method a combination of factor analysis and multiple regression (Dash & Paul, 2021).

3.5 Sampling

On the campus of the Radboud University, based in The Netherlands, individuals are asked to participate in the experiment. Since all participants are picked at the Radboud University campus and not every individual in the population has an equal chance of being selected to participate in the experiment, the non-probability sampling technique is used. Out of the types of non-probability sampling, the judgement sampling method is utilized. Considering the fact that the experiment takes place on the Radboud University campus and all participants are selected from the student population present at the time of the experiment, judgement sampling is the most appropriate method to be used (Tyrer & Heyman, 2016).

3.6 Research Ethics

The consent form, that the participants receive before the experiment, states that by signing the form, the participants give permission to the researchers to use the data that is collected from them. Furthermore, in order for the individual participant's data to be untraceable, no names are used during or around the experiment. The participants are only assigned to a participant ID. Apart from filling in their age and name on the consent form, the participants are not asked to fill in any personal data. As the consent form is not connected to a participant ID, the experiment data is collected totally anonymously. The data is only shared between the researchers involved in the experiment and is handled confidentially, since it is exclusively used to answer the research question and is not used for secondary purposes. Finally, participants have the right to withdraw from the experiment at every point in time.

4. Research Results

To analyse the data of the experiment, IBM SPSS Statistics version 29, and SmartPLS were used. To check the descriptive statistics and to reverse code some of the items of the dataset, SPSS was used. Subsequently, SmartPLS was used to validate and evaluate the measurement and structural models by examining their validity and reliability statistics. Additionally, the structural model was evaluated to test the formulated hypotheses.

4.1 Data Preparation

4.1.1 Cleaning the data and manipulation check

Before performing data analysis in SmartPLS, the data required cleaning. The cleaning process was conducted in Excel, where unusable data was reported as missing data. Data was considered unusable if a participant for example answered a question with '9', when the measurement scale's maximum was '7'. Then, a dummy variable was created for the manipulation of personalization. Next, three items in total were reverse coded in SPSS to make sure every statement was either positively or negatively formulated.

<u>*Manipulation check pre-test*</u>

In order to check whether the GenAI-Personalization manipulation worked, a pre-test was performed. Therefore, a confirmatory factor analysis was conducted in SPSS to see if the items of *GenAI-Personalization* are reliable indicators. Appendix 11 shows this factors analysis. Both the KMO measure (.475) and Bartlett's Test (.136) did not meet the criterion of >.50 and significance, respectively (Field, 2013). Whereas the factor loadings were satisfactory (<.50), not all item communalities were above the satisfactory threshold of >.50, ranging from 0.344 to 0.747. However, due to the low number of items, none were deleted. Furthermore, Cronbach's alpha for *GenAI-Personalization* was found to be (.524), which is below the threshold of .70 as suggested by Field (2017). This indicates that the internal consistency is relatively low, However, this is possibly caused by the low number of questions, only three, representing the manipulation. If the number of test items is too small, it may result in an underestimation of reliability, meaning that reliability could be higher than portrayed (Tavakol & Dennick, 2011). Next, the manipulation check was performed with an independent sample t-test. For *GenAI-Personalization*, there was a statistically significant difference between personalized (M = 5.63 and SD = 0.62) and non-personalized (M = 3.87 and SD = 0.79), p = <.001). Therefore, the manipulation of *GenAI-Personalization* was successful. The full results are presented in Appendix 11.

Manipulation check experiment

To evaluate whether the manipulation of *GenAI-Personalization* worked properly, a manipulation check of the actual experiment was conducted. Before conducting the manipulation check, a confirmatory factor analysis was performed in SPSS to verify whether *GenAI-Personalization* was a reliable construct with the items used. Details of this factor analysis are provided in Appendix 12. The KMO measure (.664) and Bartlett's test (<.001) met the criterion of >.50 and significance, respectively (Field, 2013). In addition, the communalities and factor loadings exceeded the threshold of >.30 and >.50, respectively as well (Field, 2013). Next, the manipulation check was conducted by using an independent sample t-test in SPSS (see Appendix 12). The results showed a statistically significant difference between the personalized ($M = 5.22$ and $SD = .84$) and non-personalized ($M = 3.34$ and $SD = 1.01$) conditions, $p < .001$. Therefore, it can be concluded that the manipulation of *GenAI-Personalization* was successful. The complete results of the manipulation check are presented in Appendix 12.

4.1.2. Missing data analysis

Using SPSS, a missing data analysis was performed. Data was collected from a sample of 117 valid respondents studying at Radboud University. During the experiment, respondents completed a questionnaire, resulting in 117 collected responses. The sample was representative for Radboud University students considering *gender*, *age*, *faculty of study* and *English language proficiency*. This indicates that the sample accurately reflects a larger student population. Therefore, the missing data in the sample represents observation not included in the initial sample. Next, the extent of missing data was determined. The SPSS output (Appendix 13) indicates that no individual case exceeded the 10 percent threshold, as described by Hair et al. (2019), suggesting that the missing data can be considered negligible. Furthermore, Little's MCAR test was conducted (Appendix 13, Table B) and found to be not significant at an alpha level of >.05, indicating that the missing data is completely at random.

4.2 Evaluation of the measurement model

The assessment of the measurement model is performed using SmartPLS by conducting a confirmatory factor analysis and examining statistics related to factor loadings (convergent validity), construct reliability, and discriminant validity. For factor loadings, a minimum threshold of 0.5 is recommended, with an optimal loading being 0.7 or higher (Hair et al., 2019, p. 663). All factor loadings were higher than 0.5, except for AIAT4 (.278). Therefore, that item was deleted. After the deletion of AIAT4, the factor loadings ranged from 0.624 to 0.908, meeting the minimum required threshold. Additionally, construct reliability indicators, measured by Composite Reliability (CR), are considered acceptable for a value of 0.7 or higher (Hair et al., 2019, p. 663). The CR values for the constructs of this study range from 0.779 to 0.805, indicating an acceptable reliability. In this case, the

CR value ‘Rho C’ is utilized, since this does not assume the equal contribution of each item to the construct (Achjari, 2015). Moreover, convergent validity is measured by the Average Variance Explained (AVE) metric and should be higher than 0.5 (Hair et al., 2019, p. 663). The AVE values for the constructs of this study were 0.547 for *hedonic value* and 0.585 for *attitude towards AI*, indicating a sufficient convergent validity for both *hedonic value* and *attitude towards AI*. Finally, discriminant validity is evaluated through the Heterotrait-Monotrait (HTMT) correlation ratio, where HTMT values should be lower than 0.85 (Hair et al., 2019, p. 776). In this study, all HTMT values were below the threshold of 0.85. Therefore, it can be stated that all constructs included in the HTMT analysis confirmed discriminant validity. A summary of the constructs, including the corresponding composite reliability values, convergent validity values, and factor loadings, can be found in Appendix 20. Finally, the model fit was evaluated using the Standardized Root Mean Square Residual (SRMR). Since for the SRMR, it is still unclear whether the saturated or the estimated model should be taken into account (Ringle, 2022), both models were evaluated. Values below 0.08, 0.10 and above 0.10 indicate a good, moderate and poor fit, respectively (Hu & Bentler, 1999). The SRMR value for the saturated model was 0.078, below the desirable threshold of 0.08, indicating a good fit. Nevertheless, the SRMR for the estimated model was 0.124, above the 0.10 threshold, suggesting a poor fit. On average, the model can be a considered a moderate fit. Additionally, the Goodness-of-Fit (GoF) Index was used to evaluate the model fit. According to Wetzels et al. (2009), 0.1 is the small threshold, 0.25 is the medium threshold, and 0.36 is the large threshold. This model has a GoF Index of 0.23, which is considered is considered a small model fit, almost exceeding the medium fit threshold. The calculation of the GoF Index is presented in Appendix 20, Table A.

4.3 Evaluation of the structural model

4.3.1 Collinearity and Coefficient of Determination

Examining the collinearity among predictor constructs is necessary as it prevents potential bias in the path coefficients (Hair et al., 2019, p. 790). This assessment is performed by examining the Variance Inflation Factor (VIF) values. The VIF Values should ideally remain below the threshold of 3.0. As visible in Appendix X, Table X, all VIF values are below 3.0, indicating no issues with collinearity and meeting the criterion. Next, the coefficient of determination (R2) is examined, which is a measure of the model’s predictive power. A higher R2 indicates a stronger explanatory power of the model and thus better prediction of the dependent variable (Hair et al., 2019, p. 260). Nevertheless, in this research, the adjusted R2 is examined, since this value takes the sample size and complexity of the model into account (Hair et al., 2019, p. 260) and therefore is the recommended statistic (Heinzl & Mittlböck, 2002). An adjusted R2 of 0.01 is considered weak, 0.09 moderate, and 0.25 strong (Jacobs & Korzilius, 2022). Based on these thresholds, the constructs *action taken to improve financial literacy* (0.176) and *hedonic value* (0.024) have moderate predictive power. The construct *cognitive* *load,* measured by fixations per second, has a negative adjusted R2, indicating that there is no explained variance at all (Heinzl & Mittlböck, 2002). For that reason, this construct is deleted from the analysis.

4.3.2 Effect sizes

According to Hair et al. (2019, p. 780), effect size is explained as ‘’The effect size represents the change in the R2 value when a specified exogenous construct is omitted from the model.’’ The appropriate measure for this purpose is Cohen’s f2. Effect sizes are indicated as weak (0.02), moderate (0.15) and strong (0.35), respectively. An effect smaller than 0.02 indicates that there is no effect (Hair et al., 2019, p. 780). In this research, the effect sizes range from 0.048 to 0.169. The smallest effect size observed is from the moderating effect of *attitude towards AI* on the relationship between *GenAI-personalization* and *hedonic value* (0.048). The largest effect size observed is from *GenAI-personalization* to *action to improve financial literacy* (0.169). All effect sizes are provided in Appendix 20, Table B.

4.3.3 Path coefficients

Path coefficients are the values representing the magnitude of the relationships between the constructs within the model (Hair et al., 2019, p. 762). In SmartPLS, these path coefficients are standardized to make comparison easier (Hair et. al, 2019, p. 208). Consequently, a higher path coefficient (ßeta coefficient) indicates a stronger relationship compared to a lower path coefficient when significant. The outcomes of the structural model evaluation can be found in Figure 2 below.

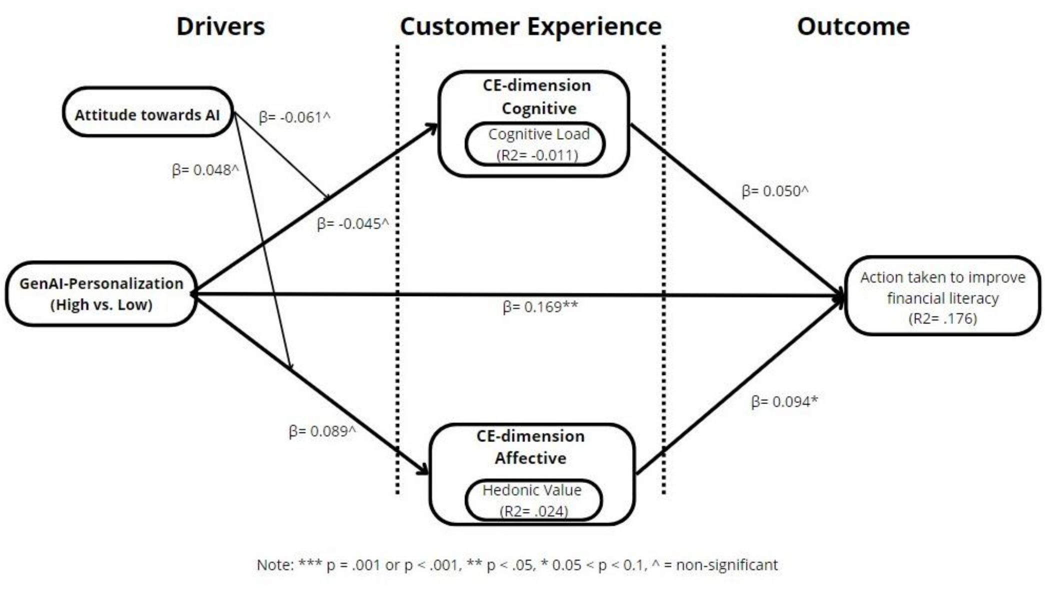

Figure 2

Before doing the analysis, a dummy variable was created for *GenAI-Personalization*, resulting in that a score of '0' meant no personalized content and a score of '1' meant personalized content. The results of the analysis indicate a statistically significant, positive effect of *GenAI-Personalization* on *action taken to improve financial literacy* (ß = 0.169; p = .038; R2 = .226). For that reason, H1 is supported. Moreover, there is a statistically insignificant effect of *GenAI-Personalization* on *cognitive load* (ß = -0.045; p = .807; R2 = .015). Therefore, H2a is not supported. Additionally, there is a statistically insignificant effect of *GenAI-Personalization* on *hedonic value* (ß = 0.089; p = .641; R2 = .049). Subsequently, H2b is not supported. There was a statistically insignificant moderation effect of *attitude towards AI* on the relationship between *GenAI-Personalization* and *cognitive load* (ß = -0.045; p = .835; R2 = .014). For that reason, H3a is not supported. There was a statistically insignificant moderation effect of *attitude towards AI* on the relationship between *GenAI-Personalization* and *hedonic value* (ß = 0.048; p = .819; R2 = .049). Therefore, H3b is not supported. Next, there was a statistically insignificant effect of *cognitive load* on *action taken to improve financial literacy* (ß = 0.050; p = .151; R2 = .226). Thus, H4a is not supported. Finally, the results indicate was a positive effect of *hedonic value* on *action taken to improve financial literacy* (ß = 0.094; p = .060; R2 = .226). However this does not meet the common threshold for statistical significance of p < .05, it can be considered marginally significant, as in this thesis, p-values between 0.05 and 0.10 are referred to as 'marginally significant', indicating a trend towards statistical significance. Subsequently, H4b is marginally supported.

4.3.4 Additional analysis

Given the initial results, where most outcomes were found statistically insignificant, an additional outcome variable, *learning motivation*, was introduced. The additional analysis explored the effects of the other constructs on *learning motivation*, aiming to uncover any underlying relationships that could not be found with the initial model. The results showed a statistically significant, positive effect of *GenAI-Personalization* on *learning motivation* (ß = 0.549; p = .001; R2 = .330). In addition, there was a statistically significant, positive effect of *hedonic value* on *learning motivation* (ß = 0.406; p < .001; R2 = .330). Finally, despite cognitive load not explaining a significant variance in the overall model, there was a statistically significant, negative effect of *cognitive load* on *learning motivation* (ß = -.209; p = .008; R2 = .330).

<u>*Control variables*</u>

The path coefficients and their associated p-values are presented in Appendix 20, Table B. In terms of control variables, a dummy variable was made for *gender*, transforming the answers 'Male, Female or Other' into '0' for female and 'other' participants and '1' for male participants. This was done since there were no participants that identified as 'other'. Results showed that *gender* has a statistically significant, positive effect on *action taken to improve financial literacy* (ß = 0.289; p < .001; R2 =

0.226). In addition, a dummy variable was made for *faculty of study*, since a the majority of the sample consisted of management students. Therefore, management students were labelled as '1' and students from other faculties as '0'. Results showed that the control variable *faculty of study* has a statistically significant, positive effect on *action taken to improve financial literacy* (ß = 0.152; p = .036; R2 = 0.226). The other control variables demonstrate a statistically insignificant effect on *action taken to improve financial literacy*. The SmartPLS structural model can be found in Appendix 14.

5. Conclusion and Discussion

The main findings of this study provide insights into how personalization is experienced in a GenAI educational context, regarding the role of the affective and cognitive customer experience dimensions in this relationship, and how this personalization affects the behavioural outcome of taking action to improve financial literacy. This study specifically examines how personalization in a GenAI financial education context affects the *cognitive load* and *hedonic value* of individuals (also with *attitude towards AI* as a moderator), and how this personalization affects the behavioural outcome of taking *action to improve financial literacy*. Therefore, this study answers the following research question: 'What is the role of *cognitive load* and *hedonic value*, of respectively the cognitive and affective dimensions of customer experience, in the relationship between *Generative-AI personalization* and *taking action to improve financial literacy*, and how does *attitude towards AI* influence this relationship?'. First, the degree of personalized content delivered by the GenAI avatar directly influences action taken to improve financial literacy. Next, the level of personalization was does not affect participants *cognitive load* during the educational session, neither does it affect the *hedonic value* experienced by participants. Furthermore, there was no moderation effect of *attitude towards AI* on neither the relationship between personalization and *cognitive load*, nor the relationship between personalization and hedonic value. Lastly, *cognitive load* does not affect *action taken to improve financial literacy*, but *hedonic value* does have a marginally significant effect on *action taken to improve financial literacy.*

5.1 Discussion

The research results provide an answer to the research question of how the level of personalization affects the customer experience, how both influence people's action to improve their financial literacy, and how this is moderated by their *attitude towards AI*. The most important results are displayed in Figure 2. First, the results support the positive direct effect of *GenAI-personalization* on *taking action to improve financial literacy*, in line with Cordova and Lepper (1996), and Alamri et al. (2020). Thus, it can be concluded that providing personalized educational content positively influences people to improve their financial literacy. Second, no effect *of GenAI-personalization* on *cognitive load* was found, which does not align with Sun and Yu (2019), and Zhong (2022). Nevertheless, the fact that these results do not align may be due to the very specific and unique educational GenAI context of this study, which has not been researched thoroughly yet. In addition, as mentioned before, *cognitive load* could not explain any variance in this study. Third, the results did not provide evidence for an effect of *GenAI-personalization* on *hedonic value*, which contrasts with Rose et al. (2012) and Tyrväinen et al. (2020). As mentioned before, this may be due to this study being one of first researching the effect of personalization on *hedonic value* specifically. Fourth, no moderation effect of *attitude towards AI* on the relationship between *GenAI-personalization* and *cognitive load* was found, contrasting findings by

Sun and Yu (2019), Tyrväinen et al (2020), and Kim and Kankanhalli (2009). However, this may also be due to the specific researching context, which differs from previous studies. Additionally, the fact that *cognitive load* could not explain any variance could also have influence again. Fifth, the results did not provide evidence for a moderation effect of *attitude towards AI* on the relationship between personalization and *hedonic value*, which does not align with Chi et al. (2022) and Longoni and Cian (2022). This might be because people do not necessarily consider their opinion about AI when receiving the educational service. Sixth, no effect of *cognitive load* on *action to improve financial literacy,* opposing the findings of Hughes et al. (2018), Schunk et al. (2008), and (Hartley, 1999). Again, the results may have been caused by *cognitive load* failing to explain variance. Seventh, there was a marginally significant effect of *hedonic value* on *action taken to improve financial literacy*, which aligns with Ekawati et al. (2021) and Desai (2019). Despite, its marginal significance, this suggests that an increase in *hedonic value* may positively influence people to improve financial literacy.

5.2 Theoretical implications

While prior research (Baidoo-Anu et al., 2023; Holmes et al., 2023) has acknowledged the high potential of AI tutoring in education, and some studies have explored the effect of personalization on education (Carpena et al., 2019; Willis, 2011), very limited research has been done on the impact of personalized AI content in an educational context. This study offers rich insights into the impact of GenAI-personalized content in financial education, considering both the cognitive and affective dimensions of customer experience represented by *cognitive load* and *hedonic value*, respectively. Thus, this study adds to the existing literature in both customer experience and GenAI. The key findings demonstrate that *GenAI-personalization* positively influences students' efforts to improve their financial literacy, expanding the existing evidence provided by Cordova and Lepper (1996) and Alamri et al. (2020). Furthermore, the absence of a moderation effect of *attitude towards AI* on the relationship between *GenAI-personalization* and the customer experience elements suggests that individuals' *attitudes towards AI* are unlikely to influence their learning processes or customer experience. Moreover, this research suggests a, however marginally significant, positive impact of *hedonic value* on financial literacy improving behaviour in specific contexts, highlighting the need to further investigate *hedonic value,* especially in educational contexts. However no effects of *cognitive load* could be supported, this study might encourage other researchers to explore that aspect of customer experience more thoroughly. Concluding, this study contributes to both the fields of customer experience and AI, providing valuable insights for researchers aiming to optimize learning experience, customer experience, and enhance financial literacy.

5.3 Practical and managerial implications

The research findings have several practical or managerial implications. Given the evidence supporting *GenAI-personalization*'s positive influence on individuals' behaviour to improve financial literacy, managers in the educational sector are encouraged to implement more personalized content into financial literacy programs. In addition, managers can take into account that individuals' *attitudes towards AI* do not significantly influence the effectiveness of the educational content or the customer experience, indicating that people's opinions on AI do not play a crucial role in the effectiveness of educational programs. Moreover, this study creates awareness for the marginal positive relationship between *hedonic value* and financial literacy improving behaviour. In other words, managers could start experimenting with hedonic traits in educational programs, as it might influence individuals to improve their financial literacy. In conclusion, the results of this study can be valuable for managers, especially in the educational sector, as they provide evidence for *GenAI-personalization*'s positive influence on individuals' efforts to improve financial literacy.

5.4 Limitations and future research

While this study presents in-depth insights into how individuals experience personalization in a GenAI educational context, specifically regarding the role of the affective and cognitive customer experience dimensions and their impact on behaviour, there are some limitations to the study. First, this study only focuses on the effects of personalization within a GenAI educational context. Given the specificity of this context, the effects of personalization cannot be generalized to other contexts, such as advertising. Therefore, future research should investigate the effects of personalization in different contexts to obtain a broader understanding of the subject. Second, the study only examines two of the five customer experience dimensions. As a result, the customer experience is not studied as a whole. In order to gain a comprehensive understanding of customer experience, future research should explore how personalization affects the other customer experience dimensions in a GenAI educational context and how these interact. In addition, since this research only found a marginally significant effect of *hedonic value* on the behavioural outcome, future research should research this element of the affective dimension more thoroughly. Third, the sampling method used was judgment sampling. Since the participants were based on the researcher's judgment, the sample might not be representative of the broader population, leading to sampling bias might. Therefore, future research should aim to randomize the sample and increase generalizability of the sample. Lastly, the right eye-camera of the eye-tracker occasionally experienced some technical defects during the experiment, resulting in poor or no recording. Consequently, only the data from the left eye-camera has been examined in this research, which might have influenced the results. Hence, future research should work with properly working eye-tracking equipment to avoid results being affected by technological defects. In addition, while the eye-tracking data was supposed to provide valuable insights into *cognitive load*, none of the hypothesis regarding that subject were significant. Therefore, future research should also include eye-tracking measures to explore *cognitive load* in an educational context.

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7. Appendices

Appendix 1. Operationalization table

Table A. Operationalization table

Construct	Operationalization	Measure	Source
CE-Affective *Hedonic value*	- "Overall this experience was displeasing" - "In the end you felt the experience was enjoyable" - "This experience left me feeling very happy"	Seven-point Likert scale Seven-point Likert scale Seven-point Likert scale	Batra and Ahtola (1991)
CE-Cognitive *Cognitive load*	- Fixation rate	Eye-tracking	Zagermann et al. (2016)
Behaviour/Outcome *Action taken to improve financial literacy*	- Taking a financial information flyer (yes/no)	Behavioural measure	Morales et al. (2017)
Moderator *Attitude towards AI*	- AI has more advantages than disadvantages - I am afraid of AI and its future developments - I have a positive attitude towards AI - I would rather avoid interacting with technologies that are based on AI	Seven-point Likert scale Seven-point Likert scale Seven-point Likert scale Seven-point Likert scale	Stein et al. (2024)

Control variables	**Operationalization**	**Measure**	**Source**
Age	- What is your age?		
Gender	- What is the gender you identify with the most?	(1) Male, (2) Female, (3) Other	
English language proficiency	- Could you indicate on a scale of 1 to 7, how comfortable are you with the English language?	Seven-point Likert scale	
Faculty of Study	- Can you tell me what you are studying?	(1) Management, (2) Medical Sciences, (3) Social Sciences, (4) Science, (5) Law, (6) Arts, (7) Philosophy, Theology and Religious Studies, (8) Other.	

Appendix 2. 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

2

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 3. 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 4. 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 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. 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

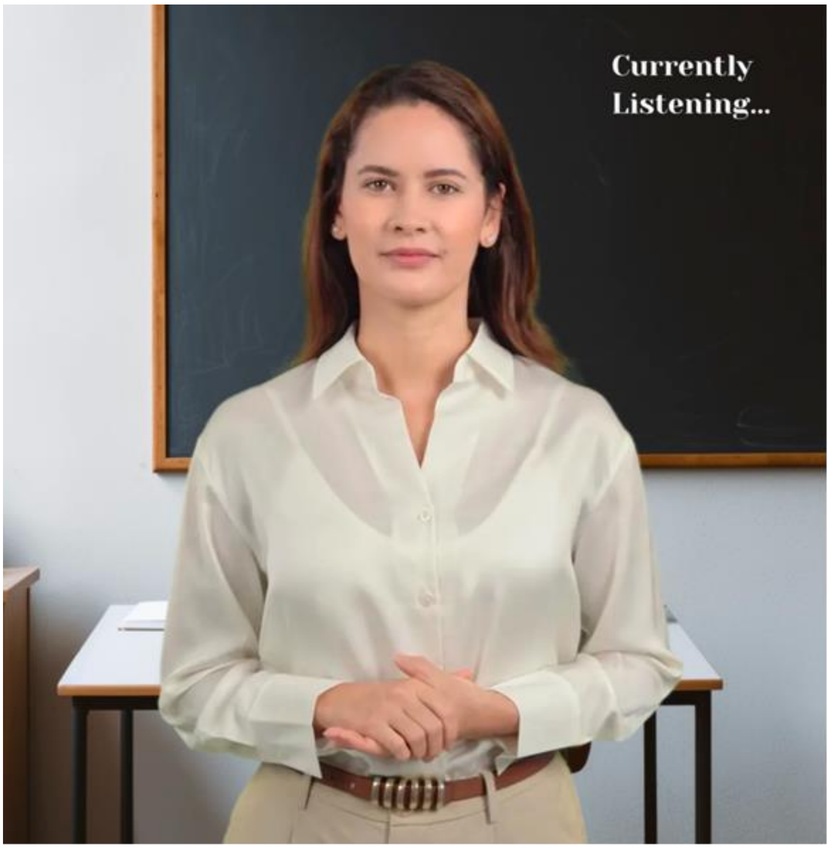
35. In the end, you felt the learning experience with me was enjoyable

36. This learning experience left me feeling very happy

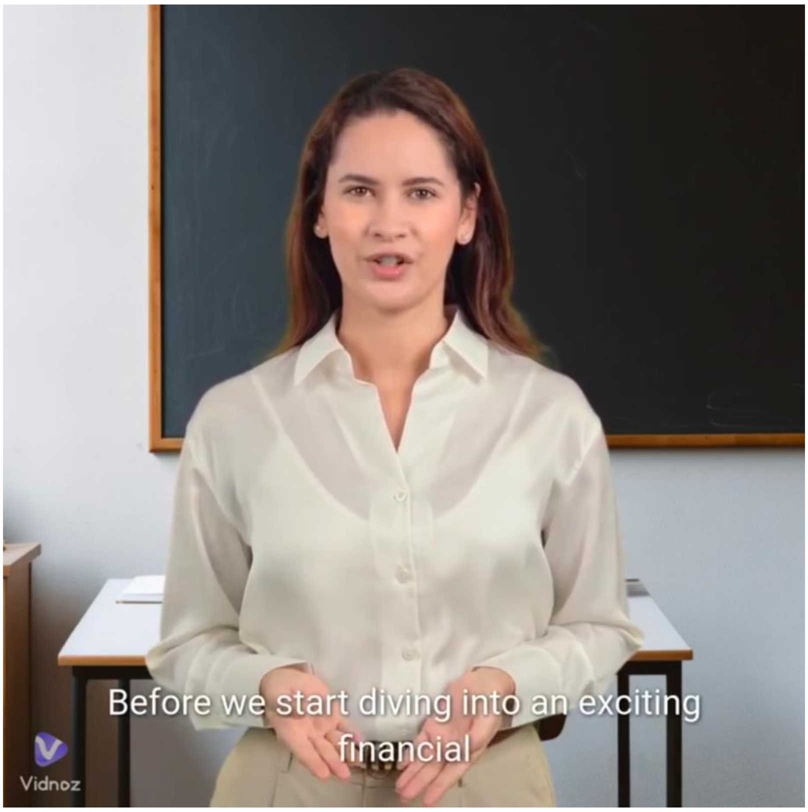
Thank you for your participation. I hope you enjoyed it and found this interaction interesting and useful. On the table to your left, you will see three flyers concerning the three main topics of financial literacy. If you think this type of education can help you in the future, please feel free to take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

Appendix 7. Mula

Appendix 8. Mula listening



Appendix 9. Mula Talking



Appendix 10: Pre-test Procedure

To measure personalization on 2 levels:

- Level 1: Personalized
- Level 2: Non-personalized

Requirements:

- Videos completed for personalization
- Videos completed to ask control variables
- Video completed to ask preferred topic
- Survey Google docs pretest
- Consent form (?)
- Teams setup
- Wheels of fortune

Scenario:

We set up the complete wizard of oz experiment

- Find 20/30 students
- Consent form
- Give them an ID number (1= personalized, 2= non-personalized)

- Start by showing the introduction videos,
- Then show the control variable questions and the question "what topic is most interesting to you"
- Then show the accompanied video or the non-personalized one
- Then we ask them to fill in the survey containing personalization and alternative explanations questions. *(The first question asks them to indicate their ID number, which enables us to split the data into (non-) personalized level)*

Survey:

Personalization (7-point Likert scale):

After being exposed to both conversations, participants were asked to rate the level of perceived personalization in each scenario from low to high on a *7-point Likert scale*, by answering the following statements:

- I feel that the AI avatar tells me information tailored to me
- The contents provided by the AI avatar were in accordance to my preferences
- The AI avatar understands my needs and wants

--> we want the mean to be significantly different from the two groups.

Alternative explanations (7-point Likert scale):

- Perceived amount of information https://doi.org/10.1016/j.chb.2020.106359
    - I felt that the amount of information I received from the AI-avatar was a lot.
- Duration of videos https://doi.org/10.1016/j.chb.2020.106359
    - I felt like the conversation with the AI avatar took a long time.
- Quality of information
    - I perceived the quality received from the AI-avatar was of high quality.
- Clarity:
    - I felt like the information was provided in a clear manner. doi:10.1016/j.jcps.2010.04.003
- Complexity
    - I find the info that was provided by the AI-avatar was complicated.

- Previous financial knowledge
    - The information provided by the AI-avatar was new to me.
- Credibility/realness of AI-avatar:
    - I felt that the AI-avatar operated like an autonomous tool.

--> we want the mean to be insignificantly different from the two groups.

Appendix 11. Pre-test manipulation check

Table A. Mean difference personalization

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

Table B. Significance of mean difference personalization

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

Table C. Descriptive statistics

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

Table D. KMO and Bartlett

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,475
Bartlett's Test of Sphericity	Approx. Chi-Square	5,544
	df	3
	Sig.	,136

Table E. Component Matrix

Component Matrix[a]

	Component
	1
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.	,587
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.	,864
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.	,682

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Table F. Communalities

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	,344
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	,747
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	,466

Extraction Method: Principal Component Analysis.

Table G: Total variance explained

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1,557	51,904	51,904	1,557	51,904	51,904
2	,957	31,902	83,806			
3	,486	16,194	100,000			

Extraction Method: Principal Component Analysis.

Table H: Cronbach's Alpha

Reliability Statistics

Cronbach's Alpha	N of Items
,524	3

Appendix 12. Actual experiment manipulation check

Table A. KMO and Bartlett

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,664
Bartlett's Test of Sphericity	Approx. Chi-Square	65,067
	df	3
	Sig.	<,001

Table B. Communalities

Communalities

	Initial	Extraction
MANI_LM_1	1,000	,578
MANI_2_R	1,000	,691
MANI_3	1,000	,630

Extraction Method: Principal Component Analysis.

Table C. Total variance explained

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1,900	63,320	63,320	1,900	63,320	63,320
2	,621	20,695	84,015			
3	,480	15,985	100,000			

Extraction Method: Principal Component Analysis.

Table D. Component matrix

Component Matrix[a]

	Component
	1
MANI_LM_1	,760
MANI_2_R	,832
MANI_3	,794

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Table E. Item-total statistics

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
MANI_LM_1	8,74	9,921	,475	,648
MANI_2_R	8,42	8,349	,578	,515
MANI_3	8,49	5,821	,527	,622

Table F. Group Statistics

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

Table G. Significance of mean difference personalization

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

Table H. Mean difference average personalization

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

Table I. Significance of mean difference average personalization

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

Appendix 13. Missing data analysis

Table A. Univariate statistics

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).

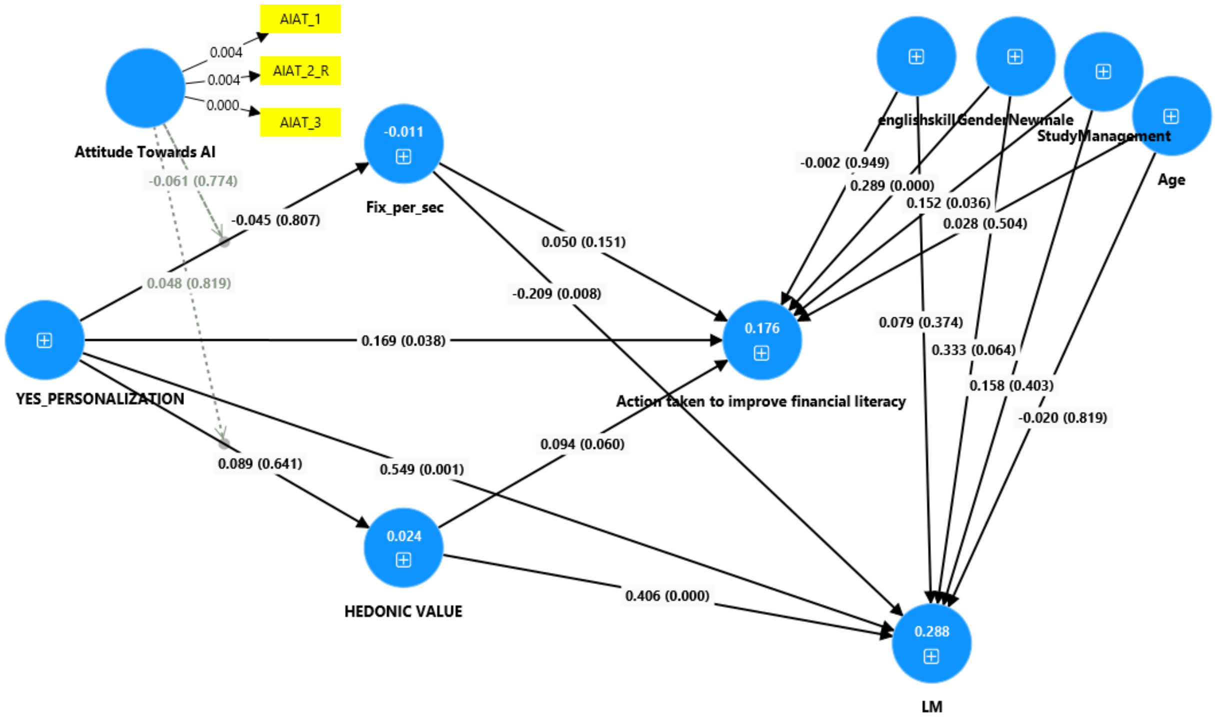
b. . indicates that the inter-quartile range (IQR) is zero.

Table B. Little's MCAR

Study	.	-,056	,113

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

Appendix 14. Measurement model



Appendix 15. Attitude towards AI

Table A. Covariance

Covariance Matrix

	AIAT_1	AIAT_2_R	AIAT_3	AIAT_4_R
AIAT_1	1,591	,557	,793	,173
AIAT_2_R	,557	2,669	,780	,505
AIAT_3	,793	,780	1,546	,241
AIAT_4_R	,173	,505	,241	1,831

Table B. Descriptives

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
AIAT_1	5,01	1,261	116
AIAT_2_R	3,99	1,634	116
AIAT_3	4,75	1,243	116
AIAT_4_R	5,06	1,353	116

Table C. KMO and Bartlett

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,629
Bartlett's Test of Sphericity	Approx. Chi-Square	58,917
	df	6
	Sig.	<,001

Table D. Communalities

Communalities

	Initial	Extraction
AIAT_1	1,000	,550
AIAT_2_R	1,000	,490
AIAT_3	1,000	,660
AIAT_4_R	1,000	,165

Extraction Method: Principal Component Analysis.

Table E. Total variance explained

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1,865	46,619	46,619	1,865	46,619	46,619
2	,967	24,168	70,787			
3	,695	17,376	88,163			
4	,473	11,837	100,000			

Extraction Method: Principal Component Analysis.

Table F. Components

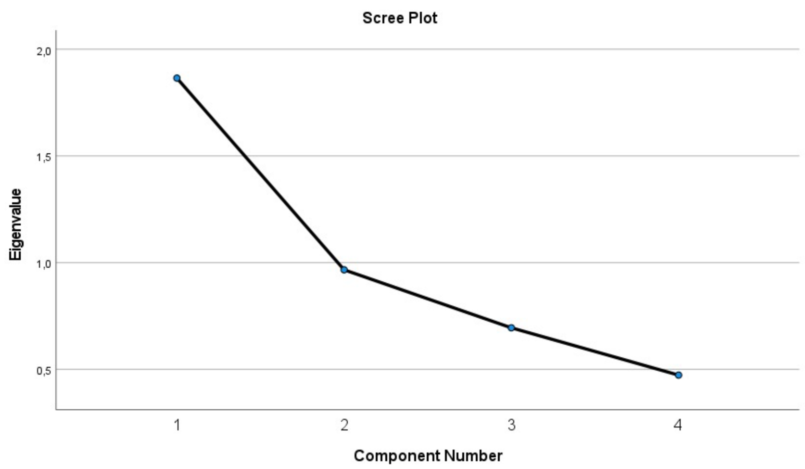
Component Matrix[a]

	Component
	1
AIAT_1	,742
AIAT_2_R	,700
AIAT_3	,812
AIAT_4_R	,407

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Figure 1. Scree Plot



Appendix 7. Hedonic Value

Table A. Descriptives

Descriptive Statistics

	Mean	Std. Deviation	Analysis N
HEDV_1_R	5,33	1,414	117
HEDV_2	4,43	1,155	117
HEDV_3	3,42	1,139	117

Table B. Covariance

Covariance Matrix

	HEDV_1_R	HEDV_2	HEDV_3
HEDV_1_R	2,000	,572	,195
HEDV_2	,572	1,333	,621
HEDV_3	,195	,621	1,297

Table C. KMO and Bartlett

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		,523
Bartlett's Test of Sphericity	Approx. Chi-Square	44,095
	df	3
	Sig.	<,001

Table D. Communalities

Communalities

	Initial	Extraction
HEDV_1_R	1,000	,362
HEDV_2	1,000	,742
HEDV_3	1,000	,545

Extraction Method: Principal Component Analysis.

Table E. Components

Component Matrix[a]

	Component
	1
HEDV_1_R	,602
HEDV_2	,861
HEDV_3	,739

Extraction Method: Principal Component Analysis.

a. 1 components extracted.

Table F. Total variance explained

Total Variance Explained

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	1,650	54,995	54,995	1,650	54,995	54,995
2	,884	29,479	84,474			
3	,466	15,526	100,000			

Extraction Method: Principal Component Analysis.

Appendix 17. Relation hedonic value and behaviour

Table A. Descriptives

Group Statistics

	Behaviour	N	Mean	Std. Deviation	Std. Error Mean
HED	Yes	32	4,7500	,73324	,12962
	No	84	4,2698	,93350	,10185

Table B. Significance of mean difference hedonic value

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
HED	Equal variances assumed	2,149	,145	2,616	114	,005	,010	,48016	,18355	,11656	,84376
	Equal variances not assumed			2,913	70,993	,002	,005	,48016	,16485	,15146	,80886

Appendix 18. Relation motivation and hedonic value

Table A. Descriptives

Group Statistics

	HED	N	Mean	Std. Deviation	Std. Error Mean
LM	>= 4,00	86	4,8209	,90334	,09741
	< 4,00	30	4,0400	,95035	,17351

Table B. Significance of mean difference learning motivation

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
LM	Equal variances assumed	,184	,669	4,023	114	<,001	<,001	,78093	,19413	,39636	1,16550
	Equal variances not assumed			3,925	48,517	<,001	<,001	,78093	,19898	,38096	1,18090

Appendix 19. Personalization on Eye-tracking data

Table A. Descriptives

Group Statistics

	Personalization mani	N	Mean	Std. Deviation	Std. Error Mean
Fix_per_sec	Personalized	58	2,2667	,83791	,11002
	Non-personalized	59	2,2936	,87420	,11381

Table B. Significance of mean difference fixations per second

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
Fix_per_sec	Equal variances assumed	,116	,734	-,169	115	,433	,866	-,02684	,15835	-,34051	,28684
	Equal variances not assumed			-,170	114,927	,433	,866	-,02684	,15830	-,34039	,28672

Table C. Boxplot

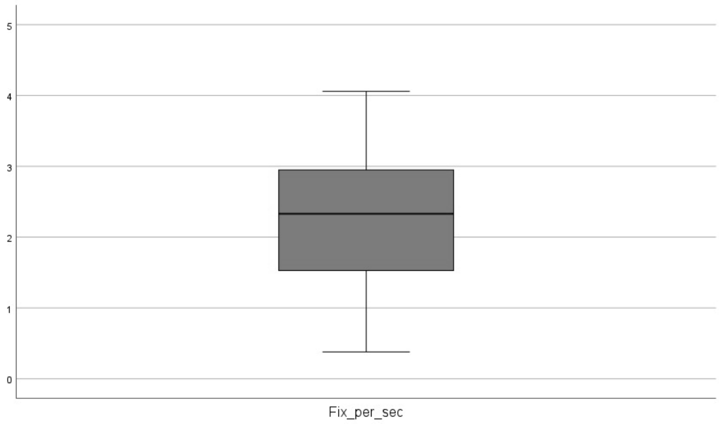
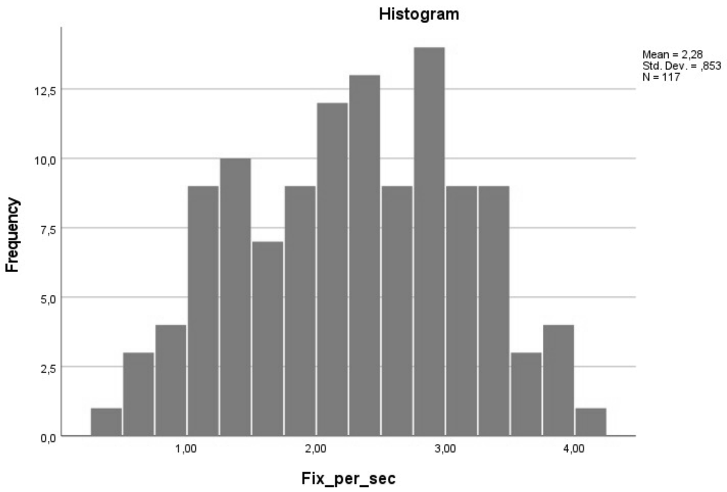


Table D. Histogram



Appendix 20. Evaluation of the structural model

Table A. Goodness-of-Fit

GoF-Index calculation:	
Mean construct communality	**Hedonic value:** (0.624*0.624) + (0.892*0.892) + (0.675*0.675) = 1.640665 1.640665 / 3 = 0.5468883333
Mean R-squared	(0.226 + 0.049 + 0.015)/3 = 0.0966666667
Mean construct communality x Mean R-squared	0.5468883333 * 0.0966666667 = 0.0528658722
GoF-Index:	√0. 0528658722 = 0.2299257972

Table B. Path coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Age -> Action taken to improve financial literacy	0.028	0.027	0.041	0.668	0.504
Age -> LM	-0.020	-0.020	0.085	0.229	0.819
Attitude Towards AI -> Fix_per_sec	-0.085	-0.095	0.161	0.531	0.596
Attitude Towards AI -> HEDONIC VALUE	0.194	0.201	0.143	1.352	0.176
Fix_per_sec -> Action taken to improve financial literacy	0.050	0.050	0.035	1.436	0.151
Fix_per_sec -> LM	-0.209	-0.204	0.079	2.664	0.008

GenderNewmale -> Action taken to improve financial literacy	0.289	0.290	0.079	3.653	0.000
GenderNewmale -> LM	0.333	0.344	0.180	1.852	0.064
HEDONIC VALUE -> Action taken to improve financial literacy	0.094	0.092	0.050	1.880	0.060
HEDONIC VALUE -> LM	0.406	0.408	0.091	4.481	0.000
StudyManagement -> Action taken to improve financial literacy	0.152	0.152	0.073	2.099	0.036
StudyManagement -> LM	0.158	0.167	0.189	0.837	0.403
YES_PERSONALIZATION -> Action taken to improve financial literacy	0.169	0.171	0.082	2.071	0.038
YES_PERSONALIZATION -> Fix_per_sec	-0.045	-0.048	0.183	0.244	0.807
YES_PERSONALIZATION -> HEDONIC VALUE	0.089	0.107	0.190	0.466	0.641
YES_PERSONALIZATION -> LM	0.549	0.562	0.173	3.181	0.001
englishskill -> Action taken to improve financial literacy	-0.002	-0.006	0.038	0.064	0.949
englishskill -> LM	0.079	0.074	0.089	0.889	0.374
Attitude Towards AI x YES_PERSONALIZATION -> Fix_per_sec	-0.061	-0.045	0.213	0.287	0.774
Attitude Towards AI x YES_PERSONALIZATION -> HEDONIC VALUE	0.048	0.076	0.209	0.228	0.819

Table C. Specific indirect effects

	Original sample (O)	**Sample mean (M)**	**Standard deviation (STDEV)**	**T statistics (|O/STDEV|)**	**P values**
Attitude Towards AI -> HEDONIC VALUE -> LM	0.079	0.086	0.067	1.173	0.241
YES_PERSONALIZATION -> HEDONIC VALUE -> Action taken to improve financial literacy	0.008	0.009	0.021	0.406	0.685
Attitude Towards AI -> Fix_per_sec -> LM	0.018	0.021	0.036	0.495	0.621
YES_PERSONALIZATION -> Fix_per_sec -> Action	-0.002	-0.002	0.011	0.202	0.840

taken to improve financial literacy					
Attitude Towards AI x YES_PERSONALIZATION -> HEDONIC VALUE -> Action taken to improve financial literacy	0.004	0.004	0.022	0.200	0.842
Attitude Towards AI x YES_PERSONALIZATION -> Fix_per_sec -> Action taken to improve financial literacy	-0.003	-0.002	0.013	0.236	0.813
YES_PERSONALIZATION -> HEDONIC VALUE -> LM	0.036	0.043	0.079	0.455	0.649
YES_PERSONALIZATION -> Fix_per_sec -> LM	0.009	0.007	0.039	0.237	0.813
Attitude Towards AI x YES_PERSONALIZATION -> HEDONIC VALUE -> LM	0.019	0.027	0.084	0.230	0.818
Attitude Towards AI -> HEDONIC VALUE -> Action taken to improve financial literacy	0.018	0.019	0.018	0.997	0.319
Attitude Towards AI x YES_PERSONALIZATION -> Fix_per_sec -> LM	0.013	0.007	0.045	0.282	0.778
Attitude Towards AI -> Fix_per_sec -> Action taken to improve financial literacy	-0.004	-0.005	0.011	0.403	0.687

Table D. Outer loadings

	Outer loadings
AIAT_1 <- Attitude Towards AI	0.719
AIAT_2_R <- Attitude Towards AI	0.642
AIAT_3 <- Attitude Towards AI	0.908
Age <- Age	1.000
Behaviouryes <- Action taken to improve financial literacy	1.000
Fix_per_sec <- Fix_per_sec	1.000
GenderNewmale <- GenderNewmale	1.000
HEDV_1_R <- HEDONIC VALUE	0.624
HEDV_2 <- HEDONIC VALUE	0.892
HEDV_3 <- HEDONIC VALUE	0.675

LM_2_R <- LM	0.662
LM_3 <- LM	0.666
LM_4 <- LM	0.816
LM_5 <- LM	0.597
MANI_LM_1 <- LM	0.797
PERSONALIZATIONN01 <- YES_PERSONALIZATION	1.000
StudyManagement <- StudyManagement	1.000
englishskill <- englishskill	1.000
Attitude Towards AI x YES_PERSONALIZATION -> Attitude Towards AI x YES_PERSONALIZATION	1.000

Table E. R-square

	R-square	R-square adjusted
Action taken to improve financial literacy	0.226	0.176
Fix_per_sec	0.015	-0.011
HEDONIC VALUE	0.049	0.024
LM	0.330	0.288

Table F. Construct reliability and validity

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Attitude Towards AI	0.654	0.807	0.805	0.585
HEDONIC VALUE	0.579	0.666	0.779	0.547
LM	0.753	0.771	0.836	0.508

Table G. Model fit

	Saturated model	Estimated model
SRMR	0.078	0.124
d_ULS	1.030	2.617
d_G	0.285	0.593
Chi-square	192.666	512.345
NFI	0.614	-0.025

Table H. Collinearity statistics (VIF)

	VIF
AIAT_1	1.356
AIAT_2_R	1.184
AIAT_3	1.475
Age	1.000
Behaviouryes	1.000
Fix_per_sec	1.000
GenderNewmale	1.000
HEDV_1_R	1.143
HEDV_2	1.450
HEDV_3	1.291
LM_2_R	1.315
LM_3	1.591
LM_4	2.125
LM_5	1.380
MANI_LM_1	1.604
PERSONALIZATIONN01	1.000
StudyManagement	1.000
englishskill	1.000
Attitude Towards AI x YES_PERSONALIZATION	1.000

Table J. Discriminant validity

	Heterotrait-monotrait ratio (HTMT)
Age <-> Action taken to improve financial literacy	0.095
Attitude Towards AI <-> Action taken to improve financial literacy	0.181
Attitude Towards AI <-> Age	0.034
Fix_per_sec <-> Action taken to improve financial literacy	0.105
Fix_per_sec <-> Age	0.133
Fix_per_sec <-> Attitude Towards AI	0.137
GenderNewmale <-> Action taken to improve financial literacy	0.297
GenderNewmale <-> Age	0.049
GenderNewmale <-> Attitude Towards AI	0.156
GenderNewmale <-> Fix_per_sec	0.032
HEDONIC VALUE <-> Action taken to improve financial literacy	0.299
HEDONIC VALUE <-> Age	0.190
HEDONIC VALUE <-> Attitude Towards AI	0.407
HEDONIC VALUE <-> Fix_per_sec	0.106
HEDONIC VALUE <-> GenderNewmale	0.148
LM <-> Action taken to improve financial literacy	0.312
LM <-> Age	0.127
LM <-> Attitude Towards AI	0.278

LM <-> Fix_per_sec	0.250
LM <-> GenderNewmale	0.125
LM <-> HEDONIC VALUE	0.590
StudyManagement <-> Action taken to improve financial literacy	0.212
StudyManagement <-> Age	0.105
StudyManagement <-> Attitude Towards AI	0.100
StudyManagement <-> Fix_per_sec	0.159
StudyManagement <-> GenderNewmale	0.047
StudyManagement <-> HEDONIC VALUE	0.325
StudyManagement <-> LM	0.219
YES_PERSONALIZATION <-> Action taken to improve financial literacy	0.159
YES_PERSONALIZATION <-> Age	0.095
YES_PERSONALIZATION <-> Attitude Towards AI	0.077
YES_PERSONALIZATION <-> Fix_per_sec	0.016
YES_PERSONALIZATION <-> GenderNewmale	0.076
YES_PERSONALIZATION <-> HEDONIC VALUE	0.069
YES_PERSONALIZATION <-> LM	0.309
YES_PERSONALIZATION <-> StudyManagement	0.094
englishskill <-> Action taken to improve financial literacy	0.075
englishskill <-> Age	0.153
englishskill <-> Attitude Towards AI	0.162
englishskill <-> Fix_per_sec	0.029
englishskill <-> GenderNewmale	0.246
englishskill <-> HEDONIC VALUE	0.262
englishskill <-> LM	0.124
englishskill <-> StudyManagement	0.110
englishskill <-> YES_PERSONALIZATION	0.230