Radboud University

Personalization of AI-generated content

Exploring the influence of personalization of AI-generated content on customer experience and the behavioral outcomes in a financial literacy context

Master thesis
MSc in Business Administration: Marketing specialization
Radboud University
Nijmegen, 17 June 2024

Author: Wessel Bom
Student number: S1107727

Thesis supervisor: Ruud Wetzels
Second examiner: Karim Sidaoui

Word count: 12883

Abstract

This thesis examines the effects of personalized AI-generated content on customer choice behavior while focusing on perceived AI usefulness and cognitive load. The study analyzes how consumers interact with AI-generated content and what their cognitive processes look like using eye-tracking technology. This research uses a between-subject experimental design, in which 117 respondents from Radboud University participated. During the experiment, the participants interacted with AI about a financial literacy topic. Personalization was manipulated to create two conditions. The findings show that personalization increases the perceived usefulness of AI, but it has no direct impact on choice behavior or lowering cognitive load. However, additional analysis showed that personalization increases the perceived AI usefulness, which subsequently raises the learning motivation. This study contributes to the existing body of knowledge by providing insights into the personalization of AI-generated content in a financial literacy context, highlighting the potential of AI to transform education by enabling more personalization and accessible learning. Finally, the findings highlight the need for more empirical research on the cognitive and behavioral effects of personalization in the AI context. This can help understand the different mechanisms underlying the customer experience and behavioral outcomes in the context of AI.

Table of content

1. Introduction **5**

2. Theoretical background **9**

2.1 Financial literacy *9*

2.2 AI *10*

2.3 Customer experience *10*

2.4 Hypotheses development *11*

3. Methodology **16**

3.1 Research Design *16*

3.2 Participants *16*

3.3 Procedure *17*

3.4 Measurement *17*

3.4.1 AI usefulness 17

3.4.2 Choice behavior 18

3.4.3 Fixations per second 18

3.4.4 Control variables 19

3.5 Data analysis procedure *19*

3.6 Research ethics *19*

4. Research results **20**

4.1 Data cleaning and manipulation check *20*

4.1.2 Missing data analysis 21

4.2 Evaluation of the measurement model *21*

4.3 Evaluation of the structural model *22*

4.3.1 Collinearity and coefficient determination 22

4.3.2 Effect sizes 22

4.3.3 Path coefficients and hypothesis testing 23

4.3.4 Additional analysis 24

5 Conclusion and discussion **25**

5.1 Discussion *25*

5.2 Theoretical implication *27*

5.3 Practical and managerial implications *28*

5.4 Limitations and future research *28*

References 30

Appendices 39

Appendix 1. Operationalization table *39*

Appendix 2. Consent form *40*

Appendix 3. Results Financial Literacy Topics Survey *41*

Appendix 4. Prompts for AI *43*

Appendix 4A: Prompt for manipulation personalized group 43

Appendix 4B: Prompt for manipulation non-personalized group 43

Appendix 5. Script AI-avatar *45*

Appendix 6. AI-avatar *51*

Appendix 7. Flyers to measure behavior *53*

Appendix 8. Data cleaning SPSS *55*

Appendix 9. Results manipulation check pre-test *56*

Appendix 10. Results of the experiment check *58*

Appendix 11. Evaluation of the model *60*

Appendix 11A: Evaluation of Measurement Model 60

Appendix 11B: Evaluation of the structural model 62

Appendix 11C. Results of the hypotheses 65

Appendix 11D: Visual representation of the model 65

1. Introduction

The outbreak of the COVID-19 pandemic in late 2019 was a turning point in global history, causing major health crises, socioeconomic disruptions, and novel difficulties for individuals and communities worldwide (World Health Organization, 2020). As the virus spread quickly across continents, its impact went far beyond public health, affecting many aspects of daily life, including the financial well-being of individuals and households. The economic consequences of the COVID-19 pandemic were severe, with firms closing, supply networks failing, and unemployment rates reaching historic highs (International Monetary Fund, 2020). Millions of people were confronted with the problems of financial insecurity such as job losses, income disruptions, and novel stress levels as they struggled with this (Lusardi and Mitchell, 2020; Fox and Bartholomae 2020). Due to inflation and rising costs of living, pursuing goals for the future has become even more challenging.

Financial literacy has emerged as a major need for people to manage the complex financial landscape resulting from the epidemic (Lusardi & Messy, 2023). Financial literacy is defined as the information and skills required to manage one's personal finances effectively and has always been a vital tool in dealing with financial challenges (Hasler et al., 2023). On average, across 39 countries and economies, 34% of adults reach a minimum target score for financial literacy, which means that the remaining 66% do not reach the minimum target score (OECD/INFE et al., 2023). For this reason, the European Union emphasizes the need for financial literacy in target groups, including younger people. Although financial literacy is becoming more widely recognized, few members of Generation Z possess these abilities (Shan et al., 2023). They further argue that a lack of knowledge can have negative effects, such as failing to see the need for retirement savings, carelessly spending money, or overpaying debt with high interest rates. This highlights the need to teach people financial literacy, which ultimately helps stabilize their financial situation and improve financial well-being (Becerra, 2019; Philippas & Avdoulas, 2021).

The current digital age comes with information overload resulting from the Internet's abundance of irrelevant information and data, overwhelming consumers (Arnold et al., 2023). By 2025, the worldwide data loop is projected to grow exponentially from 33ZB in 2018 to 175ZB in 2025 (Wu et al., 2020). With the increasing usage of information and communication technology and the digitalization of the workplace, this overload problem is worsening. Information overload is related to an increase in burnout, health complaints, individuals' quality of decision-making, and decreased efficiency of information processing (Ellwart & Antoni, 2017; Junghanns and Kersten, 2020; Phillips-Wren and Adya, 2020; Miller, 1978). This emphasizes the need for personalized content to address this issue (Arnold et al., 2023).

In recent years, the integration of AI-generated content has revolutionized the landscape of financial literacy education, providing novel methods to meet the changing needs of individuals. AI-powered tools and platforms use complex algorithms and data analytics to provide personalized financial education based on users' individual interests and situations (Shah et al., 2020). AI has been used in content generation, personalized recommendations, chatbots, image and speech recognition, and sentiment analysis (Biljman, 2023). Personalization can be used to improve students' financial literacy (Shafiee et al., 2023; Kuntze et al., 2019). Furthermore, making good use of personalization can result in a 5%-15% increase in revenue (Boudet et al., 2019). The $15.2 billion allocated to generative AI firms in early 2023, shows that the transition has generated significant investments, indicating an increase in businesses focused on AI-based solutions (Cooban, 2023). Understanding financial literacy and the use of AI personalization is crucial to the extent of the existing research on AI and its implications; however, it offers little guidance.

Personalization is currently being implemented to collect and analyze customer data to deliver tailored content to each and adapt offerings to meet customers' needs (Kalignaman et al., 2018; Oberoi et al., 2017; Lemke et al., 2011). Despite increasing investments in personalization, there is still a lack of empirical research on the impact of personalization on customer experience (CX) (Salonen & Karjaluto, 2016; Tyrväinen et al., 2020). Nevertheless, studies have found that personalization is positively related to CX (McLean et al., 2018; Pappas et al., 2017). Personalization has been established as an important strategy in digital marketing to reduce cognitive load and influence consumer behavior (Huang et al., 2023; Chandra et al., 2022). However, there is still a significant lack of empirical evidence regarding the extent and manner of AI-enabled customer experience (Ameen et al., 2021; Gao & Lui, 2022). Additionally, Burlaco & University Twente, (2023), highlighted the need for future research on AI-generated content and user engagement. This represents a significant shift in the direction of comprehending not only the existence of AI in marketing and its effects on customer experience but also its effects on customers' behavior.

In this research, the focus is on the cognitive dimension of CX, which is measured by cognitive load. AI can play a pivotal role in managing cognitive load by customizing the delivery of educational content (Willis, 2024). Furthermore, learners with personalized instructions have decreased cognitive load (Ferguson et al., 2022). This result emphasizes the need for more empirical research on the precise effects of AI-driven personalization on cognitive load in a learning context. Closing this gap helps create more efficient learning solutions using AI to fulfill personalized needs. Thus, both theoretical and managerial needs exist for research on how AI-driven personalization affects consumer cognitive load and decision-making in a financial literacy context.

Research Objective

This research aims to answer the following question: "How does personalized AI-driven content influence consumer choice behavior through the mediating effects of cognitive load and perceived AI usefulness in a financial literacy context?" The research will use eye-tracking to provide a detailed metric of fixation duration, which has been linked to cognitive functions like learning and attention (Eckstein et al., 2017; Borys & Plechawska-Wójcik, 2017; Luna, Velanova, & Geier, 2008).

Integrating eye-tracking technology into the study of CX offers an approach to understanding and measuring the cognitive load and cognitive dimension of consumer interactions with a system (Molina et al., 2024). To address these needs, this study aims to enrich the academic literature by addressing (a) the gaps highlighted by Ameen et al., (2021), Gao & Liu, (2022), and Burlco & University Twente, (2023), respectively. (b) Collecting empirical data on the extent to which personalization of AI-generated content reduces cognitive load and influences consumer behavior and (c) how AI usefulness mediates the relationship between cognitive load and consumer behavior.

Contributions

This study contributes to the validation of the theoretical frameworks by offering empirical data on the impact of personalization of AI-generated content on the cognitive load and behavior of consumers. Specifically, it addresses how personalized content influences consumer choice behavior, providing detailed insights into this mechanism. Building an understanding of these mechanisms is important for creating more personalized AI solutions that can increase user engagement (Huang et al., 2023). This study aims to improve the understanding of how the personalization of AI-generated content influences customer experience and behavior in the context of financial literacy. This contributes to the current literature by offering a specific context in which these relationships are studied.

The research provides practical relevance for marketing practitioners and organizations with a data-driven basis of insights into how the personalization of content influences customer experience and behavior, which practitioners can use to further develop their marketing strategy within this digital age of information overload. Furthermore, it helps society by enhancing the financial literacy of the population to make informed decisions, contribute to the economy, and improve financial well-being, as emphasized by Lusardi & Mitchell, (2020). As a result, this research meets the social need for financial literacy advancements, as well as having strategic importance for organizations and the AI industry. This helps bridge the gap between AI technology and practical financial education applications, showing the potential of AI to personalize learning experiences. This emphasizes the potential of AI to revolutionize education by making it more accessible and personalized to individual needs.

Filling this gap would be significantly important from an academic standpoint because it could enable critical analysis of how AI personalization impacts cognitive load and, in turn, consumer choice-making behavior. It offers new insights into the relationship and interplay between AI and consumer choice-making. Researchers can enrich the current theories on consumer behavior in the AI context and provide more comprehensive knowledge of AI-enabled customer experience and outcomes. This may result in the creation of more advanced theoretical frameworks that explain how users interact with personalized AI content.

Outline

The thesis is structured into comprehensive sections, beginning with an introduction that places this research in the context of the growing problem of information overload and the effects of the COVID-19 epidemic on financial literacy. A literature review that examines the collected research related to personalization, AI-generated content, cognitive load, and consumer behavior will come next. The empirical methodology, including the use of an eye-tracking device and AI usefulness scale evaluation, cognitive load measurement, and behavior will be covered in the methodology section. The collected data will then be presented in the results section, and the discussion will show an interpretation of these results within the context of a wider academic conversation. This will provide valuable insights and practical consequences for marketing practitioners, society, and other organizations. Finally, the study’s knowledge contributions and implications for financial literacy and AI-driven marketing are summarized in the conclusion.

2. Theoretical background

This chapter lays the foundational theories and concepts that inform the understanding of AI, consumer experiences, and behavior in the context of financial literacy. These concepts will be supported by academic literature.

2.1 Financial literacy

Financial literacy is notably lower among Gen Z compared with older generations. As a society, we need to be prepared for the next crisis. An important step in building a more resilient society is to make financial literacy a reality (Lusardi & Mitchell, 2020). Financial literacy programs should also diversify content to include understanding and managing risk and developing financial resilience (Erdem & Rojahn, 2022). Financially literate consumers can make better-informed financial decisions, build a secure financial future, and reach their own life goals, enhancing economic stability (Consumer Financial Protection Bureau, 2016; Ouachani et al., 2020). Additionally, Angrisani et al., (2023) found that financial literacy at baseline has significant predictive power for future financial fragility. This emphasizes the need for financial literacy to prevent future financial problems. For Gen-Z university students, financial literacy gives rise to financial attitudes resulting in financial well-being (Philippas & Avdoulas, 2021). Financial well-being is the belief in one's ability to maintain current and predicted ideal living standards as well as financial freedom (Brüggen et al., 2017). Therefore, the ability to make the right financial choices and decisions has gained importance in an economic environment characterized by rapid changes and increased financial uncertainty (Lone & Baht, 2022).

Various studies have been conducted on AI being used to improve literacy, especially in the healthcare sector (Liu et al., 2022). Jiang et al., (2023), state that this need for AI systems in financial literacy education is also rising as AI is used more frequently in various fields, including education and healthcare, and as more financial institutions begin to digitize their operations. Additionally, modern technology is no longer expensive or difficult to understand. All of it is, for instance, included on a smartphone that the average person can use without specialized training. This can improve the use of AI in educational settings (Murugesan & Manohar, 2019). Additionally, when technologies become easier to use, those who understand them are able to use them more effectively in their daily lives. This might provide users with opportunities, such as enhancing the understanding of financial matters and transforming the way money is managed (Murugesan & Manohar, 2019). Despite this rise, AI in the literacy context still needs further assessment (Ng et al., 2023). Additionally, AI's ability to change the landscape of financial knowledge and literacy could have future implications. In the future, AI will advance further, bringing new approaches to improving financial literacy and showing AI's enormous opportunities.

2.2 AI

Since the 1950s, advances in artificial intelligence (AI) have spread to different industries, playing a vital role in driving socioeconomic development (Goodfellow et al., 2014; Makridakis, 2017). The application of AI in education is a prime example of its revolutionary capabilities and potential. AI-powered tools use complex algorithms and data analytics to provide personalized education (Shah et al., 2020). It gives algorithms the ability to recognize, comprehend, adjust, and change themselves (Bowen & Morosan, 2018). AI technologies use sophisticated algorithms and data analytics to personalize learning experiences for each student, which improves the quality of education (Shah et al., 2020; Grassini, 2023). Because of its capacity to generate original content, generative AI has grown rapidly, signaling an evolution toward more flexible and comprehensive models (Russell et al., 2010; Goodfellow et al., 2014; Creswell et al., 2018). As AI grows in different industries, it has become increasingly important for different stakeholders to explore AI-enabled customer experiences. The integration of AI in various industries, particularly in enhancing customer experience has shown progress (Chen & Prentice, 2024). AI technologies such as machine learning and predictive analytics can significantly improve the personalization of a service, resulting in enhanced overall satisfaction (Gao & Liu, 2022). Companies anticipate customer demands more precisely and provide personalized experiences, thereby improving customer loyalty and engagement (Araro et al., 2023).

However, a cautious approach is required given how quickly AI is incorporated into daily operations. Without sufficient examination, too much reliance on AI might lead to unintended issues and increase systemic biases (Kim et al., 2023). As AI's influence grows, it is critical to be watchful and ensure that it is applied ethically and in line with human welfare. Addressing these issues is important for maintaining customer trust and ensuring the responsible use of AI (Dwivedi et al., 2021). Furthermore, AI-enabled customer experience remains underexplored and lacks empirical evidence that emphasizes the need for comprehensive studies to understand the implications and applications of AI in line with ethical guidelines and customer well-being (Ameen et al., 2021; Gao & Lui, 2022).

2.3 Customer experience

Five distinct experiences: behavioral, social, sensory, emotional, and cognitive make up the customer experiences according to several authors (Schmitt, 1999; Verhoef et al., 2009: Brakus et al., 2009). In the large body of literature on CX, academics and professionals agree that it is fundamentally a multifaceted concept comprising five components (Schmitt, 1999; Verhoef et al., 2009; Verhoef et al., 2016). First, the behavioral dimension refers to customers' behavioral responses to a firm's offerings. Second, the social dimension represents responses to the human interaction that a customer has during the experience. Third, the sensorial dimension which comprises the experience of customers related to the five senses: sight, touch, sounds, taste, and smell. Fourth, the emotional dimension is built on the generation of moods, emotions, and feelings. Fifth, the cognitive dimension consists of mental thinking evaluation processes in which customers look at the service's functional aspects.

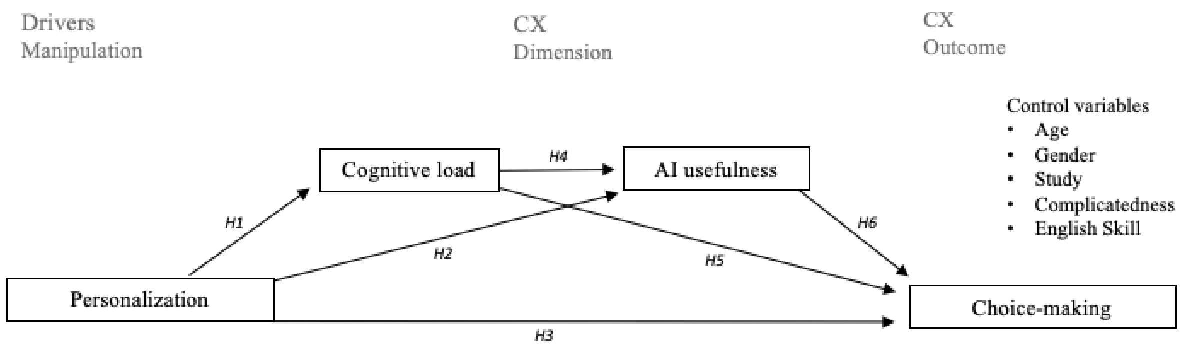
AI plays a significant role in influencing the cognitive dimension, particularly with personalization methods. AI can personalize financial education content to fit learners' preferences and level of understanding. This can increase retention and engagement because AI personalizes its content according to students' cognitive needs, which can result in increased comprehension of financial content and make learning more efficient and relevant (Das et al., 2023). AI can improve customers' cognitive processing during interactions by offering quick and relevant responses as well as personalized recommendations. With this, AI continually enhances its responses to better suit different cognitive preferences (Nicolescu & Tudorache, 2022).

As shown, with the emergence of AI, the need for more evidence of AI-enabled customer experiences increases. AI is used for content personalization. These personalized exchanges play a role in creating the customer's journey, influencing the reaction at different touchpoints, as well as the general behavioral outcomes inside an omnichannel framework (Lambillotte et al., 2022). In the context of financial literacy, this means that personalization can improve students' financial literacy. Therefore, to clarify AI's influence on customer behavior and customer experience in a financial literacy context, this research examines the complex and total interaction between personalization and the multifaceted character of CX.

2.4 Hypotheses development

The relationships between personalized content and cognitive load, cognitive load and AI usefulness, AI usefulness and decision to buy, cognitive load and decision to buy, and personalized content and decision to buy are shown in Figure 1. The following sections present the hypotheses that were established. Beginning by elaborating on the relationship between the drivers and the customer experience dimension and outcome. Second, customer experience, AI usefulness, and behavior. Finally, the relationship between AI usefulness and behavior was discussed.

Figure 1. conceptual model



Personalization

In practice, Polk et al., (2020) defined personalization as a process designed to set up a relevant, individualized interaction to enhance customer experience. During personalization, customers' personal and behavioral data are used to deliver a greater experience. Often, personalization requires customers to engage in and create personalized experiences (Lim et al., 2022). Zanker et al., (2019), argue that personalization integrates machine learning and AI into cognitive and social psychology. Firms adopt personalization as a strategy to improve convenience, lower costs, and customize the marketing mix to enhance the customer experience (Krishnaraju et al., 2013). In marketing, the cognitive load can be decreased by using personalized content and products. This reduces customer fatigue and choice-making time (Chandra et al., 2022). The lack of empirical research on AI-enabled customer experiences is emphasized by Ameen et., (2021). Accordingly, future research calls for the study of how consumers' attitudes toward personalization differ between channels such as mobile applications, online stores, and social media channels.

With the impact of personalization still emerging (Salonen & Karjaluoto, 2016; Tyrväinen et al., 2020), various studies suggest a positive relationship between personalization and customer experience, especially influencing the cognitive aspect (McLean et al., 2018; Pappas et al., 2017). This can result from using personalized content which can decrease the cognitive load while reducing customers' choice-making time and subsequently increase revenue (Chandra et al., 2022; Boudet et al., 2019). Accordingly, personalized content reduces a user's cognitive load by reducing the amount of information that they must process. Personalized content is more likely to correspond with a user's preexisting knowledge, interests, and preferences, resulting in less effort on the part of the user when filtering through irrelevant content. Personalized exchanges can help create a customer's journey and influence the reactions of consumers at various touchpoints. Additionally, it can affect general behavioral outcomes (Lambillotte et al., 2022). Drawing on the theory of personalization and its effect on cognitive load, this study aimed to determine the effects of personalization. Therefore, based on this theoretical background, the following hypothesis is proposed:

H1: Personalization of AI-generated content has a negative effect on the cognitive load of customers

The impact of personalization on various marketing metrics has been extensively studied. Personalization strategies have been used successfully, contributing to an increase in revenue and marketing efficiency (Boudet et al., 2019). According to Grewal et al., (2021), AI improves marketing effectiveness and efficiency through data-led personalization. AI can collect and analyze data faster than humans can (Ameen et al, 2021; Libai et al., 2020). Consequently, marketing activities can be personalized in terms of interface, content, and interaction processes (Hoyer et al., 2020; Zanker et al., 2019). When people believe AI systems are fair and transparent, their perceived usefulness increases, and consumers become more trusting (Shin, 2020). Additionally, Liang et al., (2009) stated that personalized services generate a higher perceived usefulness than non-personalized services. This was confirmed by Zhang et al. (2014), who emphasized that personalized services in healthcare are more useful when they adapt to specific demands and give users the impression of competence. Drawing on the studies by Zhang et al., (2014) and Liang et al., (2009), this study seeks to establish empirical evidence supporting the positive relationship between personalized AI-generated content and perceived AI usefulness. Consequently, the following hypothesis is presented:

H2: Personalization of AI-generated content has a positive effect on AI usefulness

Studies have shown that matching consumer preferences, and personalization enhances marketing outcomes (Huang et al., (2023). They further argued that personalization can influence purchase decisions. Furthermore, they underline that personalization in a marketing context can positively impact consumer behavior, through increasing engagement, purchase intention, and customer loyalty. This results in higher conversion rates because personalized content tends to meet consumer preferences more accurately. Drawing further on the study by Huang et al., (2023), Shin, (2020) and Zhang et al., (2014), the purpose of these hypotheses is to verify the beneficial effects of personalization on perceived AI usefulness and customer purchase decisions. Therefore, the following hypothesis was proposed:

H3: Personalization of AI-generated content has a positive effect on choice behavior

Cognitive load

In this study, cognitive load was used to explore the cognitive dimension of CX. It encompasses the intellectual engagement and knowledge acquisition that customers experience during their interactions with a brand or service (Brakus et al., 2009). Cacioppo & Pety, (1982) argue that intellectual engagement can comprise basic insights, learning, or engaging in advanced cognitive activities. These cognitive functions serve as crucial mechanisms for focusing attention and allowing critical evaluations of the customer experience during customer engagement (Hoch, 2002). Sweller (1988), proposed the cognitive load theory (CLT), which suggested that cognitive resources are limited. Cognitive overload can occur when information-processing demands exceed these limits. In addition, it is described as the amount of mental effort used in working memory during the execution of cognitive tasks (Fang et al, 2016) and system interaction (Sweller, 1988). The amount of mental effort required to maintain working memory is referred to as cognitive load. In terms of perceived usefulness, particularly in the context of the Technology Acceptance Model (TAM), a system's perceived usefulness may be negatively impacted by a higher cognitive load. Regardless of a system's true capabilities, if a user finds it difficult to use, they might perceive it as less useful because the work involved diminishes perceived benefits (Davis, 1989). Research by Chai et al., (2020) suggests that when educational AI systems are made simple to use and minimize cognitive load, students are more likely to find the AI helpful and to interact with it, which reflects a positive attitude toward its use. This idea is further supported by Zhang et al., (2021), who showed that an increase in cognitive load can undermine the motivation and trust required for people to embrace AI virtual assistants. As demonstrated by Pillai et al., (2020), the relationship between perceived usefulness and cognitive load is also reflected in consumer behavior. Specifically, AI systems with lower cognitive load improve shopping intentions because they are viewed as more useful. Considering these observations, it is probable that the perceived usefulness of an AI system is correlated with its cognitive requirements. While systems built to be cognitively efficient are considered more advantageous, a high cognitive load is likely to limit the benefits of AI, as perceived by users. Considering these factors, the following theory was developed:

H4: Cognitive load has a negative effect on AI usefulness

As stated by Lemon & Verhoef, (2016), customer experience may drive customers' behavioral outcomes. Examples include positive word of mouth and loyalty. As Ameen et al., (2021) show, behavioral outcomes could also consist of decisions to buy or repurchase choices. This relationship was also confirmed by Lambillotte et al., (2022), who highlighted customer experience as a determinant of consumer behavior. In this study, choice behavior is studied as an outcome of customer experience. Shahpasandi et al., (2020) provided a theoretical foundation for this. Their findings suggest that cognitive experience has a positive effect on impulse buying, meaning choices are made quickly and are influenced by the cognitive experience. Additionally, Blackley et al., (2021) showed that lowering cognitive load can improve positive affect and awareness of options when making decisions. This supports the idea that cognitive load affects choice behavior by indicating that controlling cognitive load can improve the quality of choices made. Drawing further on the finding that cognitive load may drive behavior and subsequently have a positive effect on choice behavior and buying, this research established the following hypothesis:

H5: Cognitive load has a positive direct effect on choice behavior

AI usefulness

The Technology Acceptance Model (TAM) holds that perceived utility is a key factor in determining behavioral intention and actual system use (Davis, 1989). Building on this, research from a variety of fields, including education (Hmoud et al., 2024; Jia & Tu, 2024), commerce (Pillai et al., 2020; Zhang et al., 2021), and healthcare (Tani et al., 2023), found that AI is positively correlated with higher motivation and purchase intent when it is perceived to improve performance. Remarkably, perceived usefulness influences variables such as self-efficacy and trust, and has a direct impact on attitudes and intentions (Venkatesh et al., 2003; McLean & Osei-Frimpong, 2019). Perceived AI usefulness increases learning results and engagement in educational settings (Chai et al., 2020). Commercial applications, increase shopping intentions and user acceptability (Zhang et al., 2021; Pillai et al., 2020). Therefore, the following hypothesis was proposed:

H6: AI usefulness has a positive effect on choice behavior

3. Methodology

An experiment in a constructed AI context tests the conceptual model shown in Figure 1. It is designed to help academics and researchers better understand how people experience the use of (non) customized AI-generated content to improve their financial literacy as part of their well-being.

3.1 Research Design

This research was conducted as an experiment employing the Wizard of Oz methodology. Steinfield et al., (2009), where participants believed they were interacting with AI, but the researchers controlled the device and carried out its tasks. Evaluating human behavior using the Wizard of Oz experiment has proven to be a well-established and accepted experimental design (Steinfeld et al., 2009). The experiment used a one-factor between-subjects experimental design in which personalization was manipulated (personalization: yes vs. no). In the first condition, participants encountered a personalized AI-generated video. In the second condition, they viewed a non-personalized AI-generated video. This created two conditions in which the participants were randomly assigned. To prevent biased information, the participants of the experiment were not provided with full details and information and were withheld from the actual purpose.

Scenario for the manipulation

The participants were informed that they would interact with AI to enhance their financial literacy and well-being. In the personalized condition, participants chose a topic of interest, and the AI (controlled by researchers) will show a video that explains something about the chosen topic because the participant chose their topic of interest. The AI video was specified to this person's choice, and the AI-generated video was personalized. In the non-personalized condition, participants chose a topic but received a general video instead. After the video was shown, the participants received the option to take one or more flyers about the topics that they were interested in. Researchers then observe their choices and can come to conclusions regarding the decision-making as a behavioral outcome. The results of the experiment are discussed in Section 4.

3.2 Participants

The Radboud University campus in The Netherlands is where individuals are asked to participate in the experiment. The sampling technique that will be used is non-probability sampling because the participants are gathered at Radboud University and not every single person in the population has an equal chance to participate. Within the category of non-probability sampling, the method of convenience sampling was used. Because the experiment took place at Radboud University, students are easily accessible and can experiment immediately. The participants had an average age of 22.3 years. To determine the minimum sample size in PLS-SEM, the ten-times rule method was used (Hair et al., 2019). This suggests that a minimum sample size of 30 is required. Finally, a total of 117 respondents participated in the study, which met the PLS-SEM criteria.

3.3 Procedure

The experiment was conducted in a room at Radboud University equipped with a participant computer and an eye-tracking device, the Pupil Labs Core (Pupil Labs, 2024). Researchers will monitor from a separate room from which they can implement the Wizard of Oz method. Participants will first give consent and will be asked to put their phones in silent mode. The participants were randomly assigned to one of two conditions. The participants received instructions that explained that they had to speak in English to the AI and that the rest would be clear when the experiment started. An explanation of the eye-tracker was provided. The participants then put the eye-tracker on by themselves. Next, the eye tracker was calibrated, requiring minimal head movements, only moving the eyes, and maximizing eye openness. Subsequently, the calibration was verified as success or failure. The participants were instructed to remain seated until the experiment was over and avoid touching the eye tracker. The researcher left the room and let the participants know that the experiment would start. From this moment on, the researchers in the other room started the Wizard of Oz experiment, collecting all eye-tracking data and input from the participants. When the experiment was finished, the researcher entered the room, helped the participant remove the eye tracker, and thanked them for participation. Finally, participants were offered the option to take one or more flyers about the topics discussed during the experiment, and this action was also recorded as data.

3.4 Measurement

During the experiment, one factor was manipulated, meaning that there were no measures required for this construct. The constructs of AI usefulness, cognitive load, and choice behavior were measured using existing scales from previous literature and eye-tracking technology. In Appendix 1, Table 1 shows the constructs with their operationalization. Multiple items were used to measure the factors. Eye tracking, real-time data, and a Likert scale were used to measure the different constructs and items.

3.4.1 AI usefulness

Usefulness was measured using the usefulness scale (Jahn & Kunz, 2012; Voss et al., 2003; Yuan et al, 2022). This scale consists of three items, which were measured with a seven-point Likert scale ranging from “strongly disagree” to “strongly agree” (see Table 1). The outcomes show the perceived AI usefulness of customers after the customer experience.

Table 1. AI usefulness scale

	Construct	Question	Item code	Measure	Reference
Utilitarian value	AI usefulness	The content of the AI assistant is useful	U 01	7-point Likert scale	(Jahn & Kunz, 2012; Voss et al., 2003; Yuan et al., 2022)
		The content of the AI assistant is helpful	U 02		
		The content of the AI assistant is practical	U 03		

3.4.2 Cognitive load

Eye tracking was used to measure the cognitive load by analyzing eye movements, using Pupil Labs Core glasses (Pupil Labs, 2024). The Core uses multiple resolutions and frequencies, 2 x IR eye cameras, 3D gaze rays, 3D gaze points through binocular vergence, and 2D gaze position. The results can be shown on a desktop or laptop running the Pupil Labs Core software (Pupil Labs, 2024). In this study, the fixations per second were the measurement units during the interaction with AI-generated visual content. Fixations were characterized by a focused gaze on an area of interest (AOI), and a range of 100-400ms was selected (Salvucci & Goldberg, 2000). This served as a measure of attention and cognitive processing. In this study, the overall fixations per second were operationalized as the number of times a person fixes over a specific amount of time. The periods when the eye remains comparatively still, enable the in-depth processing of visual data. Aligning with the cognitive load theory of Liu et al., (2022), an individual's level of cognitive load can be derived from the frequency of these fixations. Accordingly, fixation lengths are larger and the number of fixations per second can decrease for tasks requiring a high cognitive load. This is because deeper processing is needed, resulting in a longer duration of time spent fixating on relevant content. Conversely, a lower cognitive load leads to shorter and more frequent fixations per second, as the eye moves more rapidly across less demanding content. According to Zagermann et al., (2016), the ability to measure cognitive load in real-time allows for the dynamic adjustment of interfaces, optimizing them to correspond with the user's present cognitive capacity. Thus, using eye tracking to measure the cognitive load of the cognitive customer experience dimension allows for new insights into the difference in cognitive load between personalized and non-personalized content.

3.4.3 Choice behavior

Morales et al., (2017), suggest that the understanding of consumer behavior relies on creating realistic scenarios and measuring actual actions. Their research emphasizes the importance of matching behavioral outcomes, called dependent variables (DVs), and experimental manipulations, called independent variables (IVs), to actual settings. This will increase the validity of the study. The independent variable could be the type of experience the participants had. This can be personalized or non-personalized AI-generated content. After the customer experience, the participants were offered to take one or more flyers about the topics discussed during the experiment. This option serves as the dependent variable. This choice represents the participants' choice behavior, providing evidence of how the manipulated experience influenced their actual choice behavior. This is essential for the validation of research findings when studying consumer behavior (Morales et al., (2017).

3.4.4 Control variables

The demographic control variables age, gender, study, knowledge of the English language, and the complexity of the content were included in the study. The control variables were measured using a questionnaire during the experiment. Gender is expected to influence perceptions of AI-generated content, thereby affecting customer experience, perceived AI usefulness, and behavior. This is based on research conducted by Horowitz & Kahn., (2021), who showed that women are less likely to support the use of AI. Second, the study variable refers to the study that the participants are doing. It is expected that participants who follow a study that integrates AI more will differ more in their behavior than those who do not. The English skill and complicatedness variables are used to ensure that the customer experience and its outcomes are not influenced by these variables.

3.5 Data analysis procedure

The experimental data were analyzed using two software programs. First, IBM SPSS Statistics version 28 (IBM Corp, 2021) was used. Second, Smart PLS (Ringle, 2022). The Partial Least Squares (PLS) method can be applied to variance-based structural equation modeling using the Smart PLS method. Because PLS-SEM enables the modeling of complex relationships between observable and latent variables, it can be useful for this study. This could help understand the mechanisms by which personalization affects consumer experience and behavior. The data analysis process offered a comprehensive understanding of the interactions within the model of this study by combining these two software programs.

3.6 Research ethics

This study followed the guidelines of The Netherlands Code of Conduct for Research Integrity (2018). They defined five principles: honesty, scrupulousness, transparency, independence, and responsibility. The participants were given a consent form (Appendix 2) before the experiment, allowing researchers to use the information they provided. Data were gathered anonymously, and the participants' names were kept private. The researchers working on the study were the only ones with access to the participant data. As stated in the consent form, participants could leave at any time, even after signing the form. They are not obliged to do anything. After completing the experiment, participants received the option to provide their email addresses if they wanted to be informed about the research findings.

4. Research results

IBM SPSS Statistics, Version 28, and Smart PLS (Ringle, 2022) were used to analyze the experimental data. SPSS was used to check the descriptive statistics and reverse code items. Following, the measurement model and structural model were assessed using Smart PLS4. This involved using various statistical indicators to evaluate the validity and reliability of the models. Furthermore, an analysis of the structural model is performed to test the formulated hypotheses.

4.1 Data cleaning and manipulation check

Clean data are necessary to start with Smart PLS. Unusable data were reported as missing data throughout the data-cleaning process in SPSS. Of the 191 respondents, 74 were eliminated due to incomplete or missing eye-tracking data. In total, 117 valid respondents were included in this study. Subsequently, three questions were reverse-coded using SPSS to ensure that every statement was worded positively or negatively.

Manipulation check pre-test

A pre-test was performed to check whether the personalization manipulation worked. Personalization was measured using a preexisting scale from the literature. The scale consists of three items that measure the construct of personalization (Wong & Guan, 2018; Komiak & Benbasat, 2006). This scale is primarily used because of its established validity and reliability, guaranteeing that the measurements serve as useful indicators of the concept. The validated scales were used again, making the research findings more credible because the questions have frequently been tested and methodologically examined in earlier studies (Dale, 2006). Subsequently, an independent sample t-test (see Appendix 9) was performed to verify the efficacy of personalization modification. The results showed a statistically significant difference ($p < 0.001$) between the non-personalization group ($M = 3.86$, $SD = 0.79$) and the personalization group ($M = 5.63$, $SD = 0.62$). This important finding confirms that the manipulation was effective and guarantees that any variations in the results were caused by the manipulation and not by other influences.

Manipulation check experiment

A manipulation check of the actual experiment was performed to determine whether the personalization manipulation worked. A confirmatory factor analysis was performed before conducting the manipulation check to see whether the construct of personalization was reliable with the items that were used. Appendix 10 presents the factor analysis. KMO (.664) and Bartlett's test (<.001) met the criterion of > .50 and significance, respectively (Field, 2017). Furthermore, the communalities and factor loadings were satisfactory above the thresholds of >.20 and >.50, respectively. Cronbach's alpha was used to assess the elements that loaded highly on the components, in terms of reliability. For personalization, Cronbach's alpha was satisfactory (.688 > .60), and SPSS was used to perform an independent sample t-test to verify the manipulation (see Appendix 10). There was a statistically significant difference between personalization (M= 5.22, SD=0.83) and non-personalization (M=3.45, SD=1,00), $p < .001$. From this, it was concluded that the manipulation of personalization was effective during the experiment. Appendix 10 presents the complete manipulation check findings.

4.1.2 Missing data analysis

SPSS was used to perform a missing data analysis. The first step involved determining the type of missing data. A total of 191 participants completed the experiment. However, 74 cases had to be removed due to missing or incomplete eye-tracking or survey data. This resulted in 117 valid participants with at least one eye-tracking measurement. Three reversed items were used and recoded using SPSS because inconsistencies may occur if respondents tend to agree or select positive answers without careful consideration (Weijters & Baumgartner, 2012). The SPSS output (Appendix 8) shows that the percentage of missing data for each item was 10 percent or less as described by Hair et al., (2019). This indicates that the missing data are accepted and can be ignored (Lee & Huber, 2021). Little's MCAR test (X = 102,889, DF=93, $p <.277$) was not significant at an alpha level of .05 (see Appendix 8, Table 2). This means that the missing data can be interpreted as Missing Completely at Random (Sainani, 2015).

4.2 Evaluation of the measurement model

The assessment of the measurement model within Smart PLS involves executing a confirmatory factor analysis (CFA) and reviewing factor loadings for internal reliability, construct reliability, convergent validity, and discriminant validity. Factor loadings should ideally be 0.70 or higher, although a minimum of 0.5 is acceptable (Hair et al, 2019, p. 663). The values for construct reliability should be above 0.70 (Hair et al., 2019, p. 663). Furthermore, convergent validity is measured with the Average Variance Explained (AVE), which should be above 0.50 (Hair et al., 2019, p. 663). Finally, discriminant validity was assessed using the Heterotrait-Monotrait (HTMT) ratio of correlations, with a recommended threshold below 0.85 (Hair et al., 2019, p. 776). Next, the model shows that all factor loadings are above the threshold of 0.5, and most are ideally with a loading above 0.70 or higher (see Appendix 11A, Table 1). The construct reliability was confirmed with all the values above 0.70 (Table 2). Additionally, convergent validity was validated using the Average Variance Explained (AVE). The values for these constructs were all above the threshold of .50 (Table 2). Discriminant validity was achieved because none of the HTMT values exceeded the threshold of 0.85. (Table 3).
Appendix 11A, Tables 5 and 6 display a summary of the constructions together with the corresponding composite reliability values, convergent validity values, and factor loadings. Finally, the model fit statistic was examined using the Standardized Root Mean Square Residual (SRMR)

statistic. For this statistic, the desirable threshold for the saturated model is < 0.08 (Hair et al., 2019). This criterion was met with a desirable SRMR value of 0.07 (Table 4). This demonstrates that the measurement model fits the data well and satisfies the validity and reliability requirements. Appendix 11A shows all the outcomes of the evaluation of the measurement model. To further evaluate model fit, the Goodness-of-Fit (GoF) index was applied. According to Wetzels et al. (2009), there are three threshold sizes: 0,1 for small, 0,25 for medium, and 0,36 for large. Appendix 11A, Table 7 shows the GoF Index calculation. This model's GoF Index is 0.38, which exceeds the cutoff for a large model fit.

4.3 Evaluation of the structural model

4.3.1 Collinearity and coefficient determination

To ensure that the path coefficients are not biased, it is necessary to evaluate collinearity between the constructs in the structural model using PLS-SEM. The Variance Inflation Factor (VIF) is an important metric in this evaluation (Hair et al., 2019, p.790). The threshold for the VIF values is < 3.0, and Appendix 11B Table 1, shows that all values are below this threshold, therefore this criterion is met. Next, the predictive power of the structural model was examined using the coefficient of determination (R^2). R^2 provides insight into how well the independent variables explain the variation in the dependent variables. According to Hair et al., (2019, p. 260), a higher R^2 value indicates higher explanatory power of the model. Nevertheless, for a more accurate assessment considering the complexity and sample size of the model, adjusted R^2 values are preferred, because they provide a more reliable estimation by adjusting for the number of predictors in the model (Hair et al., 2019, p. 260). Therefore, the adjusted R^2 value was used in this study. The thresholds for the adjusted R^2 are as follows: 0 to 0.10, 0.10 to 0.30, 0.30 to 0.50, and > 0.50 which indicate weak, modest, moderate, and strong explanatory power, respectively (Hair & Alamer, 2022). Based on this threshold, the adjusted R^2 values indicated varying levels of predictive power. The constructs Behavior (0.154) and AIU (0.226) had modest power, with values between .010 and 0.30. The construct fixations per second had a negative adjusted R^2 value (see Table 2). This indicated that there was no explained variance.

4.3.2 Effect sizes

The effect sizes of the model constructs are displayed in the f-square matrix (see Appendix 11B, Table 3). Cohen’s f2 is used to calculate the effect of eliminating an exogenous construct from the model (Hair et al., 2019, p.780). Effect sizes below 0.02 imply minimal impact, but values of 0.02 to 0.35 indicate weak, moderate, and large effects, respectively (Hair et al., 2019, p.780). The effect sizes ranged from 0.000 to 0.314. With several effects below 0.02, the majority of the effects had a minimal impact. The largest effect size was from Personalized to AIU (0.314).

4.3.3 Path coefficients and hypothesis testing

The strength of the relationships between the constructs in a model is shown by the path coefficients (Hair et al., 2019, p.762). If statistically significant, a higher path coefficient indicates a stronger relationship than a lower one. Appendix 11B shows the full report of the results obtained from the structural model evaluation.

Testing the hypothesis

The structural model analysis through Smart PLS obtained several findings regarding the hypothesized relationships within the conceptual framework for this research (Appendix 11C). Firstly, a dummy variable for personalization was created and the dummy variable "Personalized" was included in the analysis. Moving on, results show a statistically insignificant effect of personalization on cognitive load (ß= -0.032; p=0.864). Therefore, H1 was not supported. Personalization significantly affected AI usefulness (ß= 0.977; p< 0.001), supporting H2, which suggests that personalized content significantly enhances the perceived usefulness of AI. Furthermore, the dummy variable "Behavior_yes" was included, meaning that a score of 0 meant 'no behavior' and a score of 1 meant 'behavior.' Nonetheless, H3, which posited that personalized AI-generated content enhances choice behavior, was not supported because the effect was not statistically significant (ß=0.122; p=0.172). Furthermore, there was a statistically insignificant effect of cognitive load on AI usefulness (ß=0.008; p=0.923). Thus, H4 is not supported. There was a statistically insignificant effect of cognitive load on choice behavior (ß=0.060; p=0.083). Thus, H5 is not supported. Furthermore, the results show a statistically insignificant direct effect of AI Usefulness (AIU) on choice behavior (ß = 0.064; p=0.158). Based on this, H6 is not supported. Appendix 11B, Table 5 shows the serial mediation effects. None of the serial mediation effects were significant (p <0.05). According to the results stated above, none of the evaluated serial mediation pathways were statistically significant.

Control variables

The control variables were analyzed using Smart PLS (Appendix 11B, Table 4). For gender, a dummy was created, and the dummy variable "Male" was included in the analysis. Gender had a statistically significant positive effect on choice behavior (ß =0.273; p< 0.001). Furthermore, the study has a positive and significant effect on choice behavior (ß =0.185; p< 0.001). This supports the notion that gender may influence choice behavior. The dummy variable "Management" was created and included in the analysis of the control variable study. The other control variables, complicatedness, and English skills showed a statistically insignificant effect on choice behavior.

4.3.4 Additional analysis

An additional analysis included the effects of Learning Motivation (LM) as a behavioral dimension. This outcome variable was included in the structural model to compare the different outcomes within the behavioral dimension. Learning motivation is a different dependent variable in the behavioral dimension than choice behavior, and it shows different effects. There was a statistically significant effect of cognitive load on learning motivation (ß =-0.180; $p < 0.001$). Additionally, there was a statistically significant effect of AI usefulness on learning motivation (ß =0.478; $p < 0.001$). This result suggests that when AI is perceived as useful, it significantly and positively influences motivation to learn. Furthermore, with learning motivation evaluated as a dependent variable for serial mediation effects, a statistically significant indirect positive effect of personalization via cognitive load on AI usefulness was shown (ß = 0.467; $p < 0.001$). This mediation can be found in Appendix 11B, Table 5, which indicates that personalized content initially positively influences the perceived usefulness of AI, which eventually positively impacts the motivation to learn.

5 Conclusion and discussion

The primary research findings offer valuable insights into the experience of personalization In the context of artificial intelligence (AI), including its usefulness, cognitive load, and impact on customer experience outcomes, decision-making, and learning motivation. This study examines how personalization affects cognitive load and, the perceived usefulness of AI, how cognitive load affects AI usefulness, and their combined influence on choice behavior and motivation to learn in a financial literacy context. As a result, the following research question is answered within this research: “How does personalized AI-driven content influence consumer choice behavior through the mediating effects of cognitive load and perceived AI usefulness in a financial literacy context?” The findings demonstrate that, although personalization significantly increases AI’s perceived usefulness, it has no significant effect on cognitive load. This increase in perceived AI usefulness does not significantly impact choice behavior. The results show that the direct effects of personalization on choice behavior are not significantly directed through the cognitive load, as the cognitive load does not significantly mediate the relationship between personalization and AI usefulness. Furthermore, there was no significant relationship between cognitive load and choice behavior, nor was there a mediating role of AI usefulness between personalization and choice behavior. Overall, personalization significantly increased perceived AI usefulness but had no significant impact on cognitive load or choice behavior.

5.1 Discussion

The research question of this study is addressed by the findings, which show if and how cognitive load and perceived AI usefulness act as mediating variables in the relationship between personalized AI-driven content and consumer behavior. This study explains, within the context of financial literacy, how AI personalization affects cognitive load, AI usefulness, and choice behavior. The main findings of this study are presented in Appendix 11D, Figure 1, which also shows how the variables interact.

First, the results provided no support for the effect of personalization on cognitive load. This result does not align with expectations and previous studies by Chandra et al., (2022), which state that personalization can decrease cognitive load. However, this result can be attributed to the study by Gwizdka, (2010), who stated that the effectiveness of personalization in reducing cognitive load is conditional on how well the personalization integrates with the user’s cognitive processes and existing knowledge. This study’s personalization techniques probably failed to reduce the cognitive load because the content was overly general or did not consider individual characteristics (Moreno & Mayer, 2007).

Moving on, the results provided support for the strong effect of personalization on AI usefulness. This is in line with the studies by Shin, (2020), Liang et al., (2009), Zhang et al., (2014), and Huang et al., (2023), showing that when AI-driven content is personalized, the perceived AI usefulness will increase because personalization adapts the interactions to each user’s unique demands, it increases the effectiveness of AI. Users are more satisfied and trusting of AI when it provides material that matches their interests. This personalization makes the user feel understood by the AI, which increases the perceived usefulness. The strength of the effect was surprisingly strong, which implies that customers perceive AI as more useful when the content is properly personalized to meet their demands. The relevance of the content given could give an impression of competence, which is consistent with the study by Zhang et al., (2014).

Furthermore, the results provided no support for the effect of personalization on choice behavior. This is contrary to Huang et al., (2023), who highlighted the positive effect of personalization on consumer behavioral outcomes. This result could be attributed to the way in which the choice behavior was measured. Morales et al., (2017), suggest that understanding the behavior relies on realistic scenarios. This implies that the behavior could have been affected by the scenario that was created in this experiment. Additionally, it is possible that the personalization was not sufficiently in line with the participants' current interests and demands, and thus, did not create the expected behavioral outcomes.

The results provided no support for the effect of cognitive load on AI usefulness. Contradicting expectations are set by prior research, such as Zhang et al., (2021) and Pillai et al., (2020), who state that a lower cognitive load increases the perceived usefulness. This result can be explained by the participants' cognitive load, which did not reach a certain threshold necessary to significantly change their perceptions of AI usefulness (Alessa et al., 2023). Additionally, the results may have been affected by the method used to quantify cognitive load, indicating the need for different measures in the future.

Next, the results provided no support for the effect of cognitive load on choice behavior. This was not in line with the studies by Lemon & Verhoef, (2016) and Lambillotte et al., (2022), highlighting the behavioral outcomes of customer experience. This result can be explained by the study of Deck & Jahedi, (2015), who provide evidence that cognitive load harms an individual's ability to make choices effectively because making decisions with cognitive load exhausts cognitive resources and reduces the effectiveness of information processing and subsequently, decision making. However, additional analysis results support the effect of cognitive load on learning motivation. Khawaldeh & AL-Zboun, (2020), complemented this result by demonstrating the effect of an increasing cognitive load on students' decreasing motivation to learn. As the cognitive load increases, learning activities become more difficult and unpleasant, which lowers motivation. People become overwhelmed and distracted when tasks become too demanding, which negatively affects their motivation to learn.

Moving on, the results provide no support for the effect of AI usefulness on choice behavior. This can be explained by the above theory of the scenario for behavior. However, an additional analysis supports the effect of AI usefulness on learning motivation. which is in line with the studies by Venkatesh et al., (2003), Zhang et al., (2021), and Pillai et al., (2020), who state that AI usefulness increases engagement and intentions in an educational setting.

The results provided no support for the serial mediation effect of personalization on choice behavior through cognitive load and AI usefulness. This lack of support for the serial mediation effect could mean that, contrary to prior beliefs, cognitive load, and AI usefulness do not directly interact to affect decision-making. In contrast, there was a supported serial mediation effect provided by the results of the additional analysis. Personalization positively influences learning motivation, mediated by AI usefulness. This could be because personalized material makes the user feel more engaged and relevant, which improves their opinion of AI and motivates them to interact with it and perceive it as useful (Huang et al., 2023). Additionally, this positive relationship is strengthened, when the increased perceived usefulness of AI increases learning motivation by increasing engagement and motivation to learn (Zhang et al., 2021).

5.2 Theoretical implication

The conclusions of this study make a substantial contribution to the body of knowledge already available on consumer experience, behavior, and AI-driven personalization, particularly as it relates to financial literacy. Starting, the impact of personalization is still emerging, together with the lack of empirical research into AI-enabled customer experiences (Salonen & Karjaluoto, 2016; Tyrväinen et al., 2020; Ameen et al., (2021) and the integration of AI-generated content further revolutionizing the landscape of financial literacy education (Shah et al, 2020), this study on personalization and its effect on customer experience and behavior is contributing to this literature.

The findings reveal that personalization does not significantly impact cognitive load, which implies that personalization and information processing interact in a complicated way, possibly influenced by complexity or familiarity with the content (Lemon & Verhoef, 2016). Contradicting existing models of consumer behavior states that personalization effectively reduces cognitive load by simplifying decision-making processes (Chandra et al., 2022). Additionally, the strong effect of personalization on perceived AI usefulness supports previous findings on this effect in the aforementioned studies, highlighting the complexity of decision-making. This suggests that while users find personalized AI content more useful, other factors, such as trust or emotional connection, might play a crucial role in choice behavior. Understanding these factors can provide deeper insights into how consumers interact with AI and personalized content.

However, the surprising result that there was no effect on choice behavior despite increasing perceived AI usefulness, challenges prior research in this field. This demonstrates the need for further academic investigation into the conditions and mechanisms underlying how personalization influences behavioral outcomes and cognitive processes in AI-enabled environments. Furthermore, this study examined the usefulness of AI in delivering personalized content while decreasing the cognitive load.

This addresses the need for additional empirical research into the effects of personalization of cognitive load in educational settings to optimize AI personalization strategies.

The significant impact of study and gender on choice behavior supports previous findings (Cheng et al., 2013). This indicates that individual characteristics and educational background can moderate the effect on consumer behavior, suggesting that personalized strategies need to be tailored to demographic and psychographic profiles to enhance effectiveness. These contributions show that although the personalization of AI-generated content has the potential to improve financial literacy and reduce cognitive load, its efficacy depends on several variables and mechanisms. Identifying and understanding these factors can help design more effective AI systems that meet various user needs and improve the overall customer experience.

5.3 Practical and managerial implications

The results highlight the importance for practitioners and organizations to actively embrace AI-driven personalization. Personalization significantly increased the perceived usefulness of AI, although it did not lower the cognitive load or directly impact consumers' choice behavior in this context. However, additional analysis showed that when behavior was measured in terms of learning motivation, personalization positively affected this learning motivation when mediated through AI usefulness. This suggests that educational institutions and e-learning platforms should implement AI-driven personalization to enhance students' engagement, motivation, and learning outcomes. These companies should view personalization as a tool to improve consumer learning engagement, rather than relying primarily on it driving buying behavior.

In line with the aforementioned results and studies on personalization, to better meet customer demands, companies should concentrate on improving the relevance and accuracy of personalized content, while considering gender differences, rather than reducing its amount (McLean et al., 2018). Marketing teams can focus on creating content that is more personalized and tailored to different demographic factors. Given the insignificant relationship between personalization and the decision to purchase, companies in different sectors could invest more in innovative personalization technologies that adjust to users' circumstances, individual behaviors, and preferences. This may result in stronger behavioral outcomes (Lambillotte et al., 2022). In doing so, companies can use AI externally as part of a larger strategy to build lasting connections with their customers. Internally, it can be used for training and development programs that utilize personalized AI content to enhance employee learning and performance, thereby improving productivity.

5.4 Limitations and future research

Considering the results and findings of this study, several limitations and areas for future research have emerged. First, this study could not demonstrate a significant effect from or on cognitive load, suggesting a potential limitation of the measurement instrument. Therefore, future research could explore alternative variables or ways to quantify cognitive load or examine different relationships that might be stronger. Furthermore, the fact that there is no significant relationship between AI usefulness and choice behavior calls for more research on the variables that could influence this relationship (Venkatesh et al., 2003). This research focused on financial literacy as the context for examining the personalization of AI content, which may limit the applicability of the findings to other domains. Different contexts might yield different results regarding the effectiveness of personalization and its impact on cognitive load and choice behavior. Additionally, while eye-tracking and self-reported questionnaires are valid methods for measuring cognitive load, they might not fully capture the complex nature of the cognitive processes needed to interact with AI.

Future research should use additional measurements to provide a more thorough understanding. Additionally, while the results show that control variables significantly impact decision-making behavior, future research could look further into the underlying demographic and psychographic characteristics that might impact how well personalization works in commercial and educational contexts. Finally, although the relationship between personalization, choice behavior, and learning motivation has been studied, a more comprehensive model with a larger range of behavioral and psychological metrics is required to better comprehend the dynamics of AI-enabled customer experiences (Lambillotte et al., 2022). Future research may include longitudinal studies, which may result in a more detailed data capture of consumer interactions in the context of AI. Overall, further research should focus on studying cognitive and behavioral dimensions in more depth, including more eye-tracking measurements, control variables, and psychographic characteristics.

References

Ameen, N., Tarhini, A., Reppel, A., & Anand, A. (2021). Customer experiences in the age of artificial intelligence. *Computers in Human Behavior*, *114*, 106548. https://doi.org/10.1016/j.chb.2020.106548

Alessa, F. M., Alhaag, M. H., Al-Harkan, I. M., Ramadan, M. Z., & Alqahtani, F. M. (2023). A Neurophysiological Evaluation of Cognitive Load during Augmented Reality Interactions in Various Industrial Maintenance and Assembly Tasks. *Sensors*, *23*(18), 7698. https://doi.org/10.3390/s23187698

Angrisani, M., Burke, J., Lusardi, A., & Mottola, G. (2023). The evolution of financial literacy over time and its predictive power for financial outcomes: Evidence from longitudinal data. *Journal of Pension Economics & Finance*, 22(4), 640-657.

Arnold, M., Goldschmitt, M., & Rigotti, T. (2023). Dealing with information overload: a comprehensive review. *Frontiers in Psychology*, *14*. https://doi.org/10.3389/fpsyg.2023.1122200

Becerra, A. (2019). Generation Z: Social media, influencers, and brand loyalty in entertainment (Master's thesis, University of Southern California).

Biljman, T. (2023). Revolutionizing Social Media Strategy with AI: Benefits, Tools, and Challenges.

Blackley, C., Redmond, P., & Peel, K. (2021). Teacher decision-making in the classroom: the influence of cognitive load and teacher affect. *JET. Journal Of Education For Teaching/Journal Of Education For Teaching*, *47*(4), 548–561. https://doi.org/10.1080/02607476.2021.1902748

Borys, M., & Plechawska-Wójcik, M. (2017). Eye-tracking metrics in perception and visual attention research. *EJMT*, 3, 11-23.

Boudet, J., Gregg, B., Rathje, K., Stein, E., & Vollhardt, K. (2019). *The future of personalization—and how to get ready for it*, 1-7.

Bowen, J., & Morosan, C. (2018). Beware the hospitality industry: the robots are coming. *Worldwide Hospitality and Tourism Themes*, 10(6), 726-733.

Brakus, J. J., Schmitt, B. H., & Zarantonello, L. (2009). Brand Experience: What Is It? How Is It Measured? Does It Affect Loyalty? *Journal of Marketing*, 73(3), 52– 68. https://doi.org/10.1509/jmkg.73.3.52

Brüggen, E. C., Hogreve, J., Holmlund, M., Kabadayi, S., & Löfgren, M. (2017). Financial well-being: A conceptualization and research agenda. *Journal of business research*, 79, 228-237.

Burlacu, C. & University of Twente. (2023). *The impact of AI-Powered Content generation on customer experience* [Thesis]. https://essay.utwente.nl/95515/1/Burlacu_BA_IBA.pdf

Cacioppo, J. T., & Petty, R. E. (1982). The need for cognition. *Journal of personality and social*

Psychology, 42(1), 116.

Chai, C. S., Wang, X., & Xu, C. (2020). An extended theory of planned behavior for the modelling of Chinese secondary school students' intention to learn artificial intelligence. *Mathematics*, *8*(11), 2089. https://doi.org/10.3390/math8112089

Chandra, S., Verma, S., Lim, W. M., Kumar, S., & Donthu, N. (2022). Personalization in personalized marketing: Trends and ways forward. *Psychology & Marketing*, 39(8), 1529–1562. https://doi.org/10.1002/mar.21670

Chen, Y., & Prentice, C. (2024). Integrating Artificial Intelligence and Customer Experience. *Australasian Marketing Journal*. https://doi.org/10.1177/14413582241252904

Cheng, Y., Chuang, S., Wang, S., & Kuo, S. (2013). The effect of companion's gender on impulsive purchasing: the moderating factor of cohesiveness and susceptibility to interpersonal influence. Journal of Applied Social Psychology, 43(1), 227– 236.

Cooban. A, "Ai investment is booming. how much is hype?" *CNN*, July 2023. https://edition.cnn.com/2023/07/23/business/ai-vc-investment-dot-com-bubble/index.html

Consumer Financial Protection Bureau (CFPB) (2023), *Financial Literacy Annual Report*, Consumer Financial Protection Bureau. https://files.consumerfinance.gov/f/documents/cfpb_financial-literacy-fy-2022_annual-report_2023-03.pdf

Creswell, A White. T, Dumoulin. V, K. Arulkumaran, B. Sengupta, and A. A. Bharath. (2018) ."Generative adversarial networks: An overview," *IEEE signal processing magazine*, vol. 35, no. 1, pp. 53–65

Dale, A. (2006), "Quality Issues with Survey Research", *International Journal of Social Research Methodology,* 9 (2), pp. 143-158.

Das, A., Malaviya, S., & Singh, M. (2023). The impact of AI-driven personalization on learners' performance. *International Journal Of Computer Sciences And Engineering*, *11*(8), 15–22. https://doi.org/10.26438/ijcse/v11i8.1522

Davis, F. D. (1989). Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Deck, C., & Jahedi, S. (2015). The effect of cognitive load on economic decision making: A survey and new experiments. *European Economic Review*, *78*, 97–119. https://doi.org/10.1016/j.euroecorev.2015.05.004

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Williams, M. D. et al., (2021). Artificial Intelligence (AI): multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice, and policy. *International Journal Of Information Management*, *57*, 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Eckstein, M. K., Guerra-Carrillo, B., Singley, A. T. M., & Bunge, S. A. (2017). Beyond eye gaze: What else can eyetracking reveal about cognition and cognitive development? *Developmental cognitive neuroscience*, 25, 69-91.

Ellwart, T., & Antoni, C. H. (2017). Shared and Distributed Team Cognition and Information Overload. In *Advances in information quality and management* (pp. 223–245). https://doi.org/10.4018/978-1-5225-2061-0.ch010

Erdem, D., & Rojahn, J. (2022). The influence of financial literacy on financial resilience – New evidence from Europe during the COVID-19 crisis. Managerial Finance, 48(9/10), 1453–1471. https://doi.org/10.1108/mf-09-2021-0442

European Union. (2023, juli). *Monitoring the level of financial literacy in the EU.* Commission.europa.eu. https://europa.eu/eurobarometer/surveys/detail/2953

Fang, C., Jianlong, Z., Wang, Y., Kun, Y, Syed Z., Ahmad, A., Khawaji, A. (2016). *Robust Multimodal Cognitive Load Measurement*. Springer International Publishing.

Ferguson, C., Van Den Broek, E. L., & Van Oostendorp, H. (2022). AI-Induced guidance: Preserving the optimal Zone of Proximal Development. *Computers & Education: Artificial Intelligence*, 3, 100089. https://doi.org/10.1016/j.caeai.2022.100089

Field, A. (2017). *Discovering Statistics Using Ibm Spss Statistics.* sage

Fox, J., and Bartholomae, S. (2020). Household finances, financial planning, and COVID-19. *Financial Planning Review* 3 (4). https://doi.org/10.1002/cfp2.1103.

Gao, Y., & Liu, H. (2022). Artificial intelligence-enabled personalization in interactive marketing: a customer journey perspective. *Journal of Research in Interactive Marketing*, *17*(5), 663–680. https://doi.org/10.1108/jrim-01-2022-0023

Goodfellow. I, Pouget-Abadie. J, Mirza. M, Xu. B, D. Warde-Farley, S. Ozair, A. Courville, and Y. Bengio. (2014). "Generative adversarial nets," *Advances in neural information processing systems,* vol. 27,

Grassini, S. (2023). Shaping the Future of Education: Exploring the Potential and Consequences of AI and ChatGPT in Educational Settings. *Education Sciences*, 13(7), 692. https://doi.org/10.3390/educsci13070692

Gwizdka, J. (2010). Distribution of cognitive load in Web search. *Journal Of The American Society For Information Science And Technology*, *61*(11), 2167–2187. https://doi.org/10.1002/asi.21385

Hair, J. F., Black, W. C., Babin, B. J., Anderson, R. E., & Tatham, R. L, (2019). Multivariate data analysis (8th edition). Cengage Learning.

Hair, J., & Alamer, A. (2022). Partial Least Squares Structural Equation Modeling (PLS-SEM) in second language and education research: Guidelines using an applied example. *Research Methods in Applied Linguistics*, *1*(3), 100027. https://doi.org/10.1016/j.rmal.2022.100027

Hasler, A., Lusardi, A., Yagnik, N., & Yakoboski, P. (2023). Resilience and wellbeing in the midst of the COVID-19 pandemic: The role of financial literacy. *Journal Of Accounting and Public Policy,* 42(2), 107079. https://doi.org/10.1016/j.jaccpubpol.2023.107079

Hmoud, M., Swaity, H., Hamad, N., Karram, O., & Daher, W. (2024). Higher education students' task motivation in the Generative Artificial Intelligence context: the case of ChatGPT. *Information*, *15*(1), 33. https://doi.org/10.3390/info15010033

Hoch, S. J. (2002). Product experience is seductive. *Journal of consumer research*, 29(3), 448-454.

Hoffman, R. R., Mueller, S. T., Klein, G., & Litman, J. (2018). Measuring trust in the XAI context (Technical Report). *DARPA Explainable AI Program*. https://psyarxiv.com/e3kv9/download?format=pdf

Horowitz, M. C., & Kahn, L. (2021). What influences attitudes about artificial intelligence adoption: Evidence from U.S. local officials. *PLOS ONE*, 16(10), e0257732. https://doi.org/10.1371/journal.pone.0257732

Hoyer, W. D., Kroschke, M., Schmitt, B., Kraume, K., & Shankar, V. (2020). Transforming the Customer Experience Through New Technologies. *Journal of Interactive Marketing*, *51*, 57–71. https://doi.org/10.1016/j.intmar.2020.04.001

Huang, Z., Chen, G., & Zhao, G. (2023). The Effect of Personalization on Consumer Behaviors. In *Advances in economics, business and management research* (pp. 389–405). https://doi.org/10.2991/978-94-6463-246-0_47

IBM Corp. (2021). IBM SPSS Statistics for Windows, Version 28.0. Armonk, NY: IBM Corp

International Monetary Fund. (2020). World Economic Outlook: *The Great Lockdown*. Washington, DC, April.

Jahn, B., & Kunz, W. (2012). How to transform consumers into fans of your brand. *Journal Of Service Management*, *23*(3), 344–361. https://doi.org/10.1108/09564231211248444

Jia, X., & Tu, J. (2024). Towards a new conceptual model of AI-Enhanced learning for college students: the roles of artificial intelligence capabilities, general Self-Efficacy, learning motivation, and critical thinking awareness. *Systems*, *12*(3),74. https://doi.org/10.3390/systems12030074

Jiang, Q., Zak, L., Leshem, S., Rampa, P., Howle, S., Green, H. N., & Iqbal, T. (2023, April). Embodied AI for Financial Literacy Social Robots. *Systems and Information Engineering Design Symposium (SIEDS)* (pp. 220-225). IEEE. 10.1109/SIEDS58326.2023.10137791

Junghanns, G., & Kersten, N. (2020). Informationsüberflutung am Arbeitsplatz: Gesundheitliche Konsequenzen. *Zentralblatt für Arbeitsmedizin, Arbeitsschutz und Ergonomie*, *70*, 8-17.

Khawaldeh, O. A., & Al-Zboun, M. S. (2020). The effectiveness of cognitive load and internal motivation on the performance in study skills. *Khawaldeh | Journal Of Education And Practice*, *11*(4). https://doi.org/10.7176/JEP/11-4-10

Kim, J., Kadkol, S., Solomon, I., Yeh, H., Soh, J., Nguyen, T. D., Choi, J. Y., Lee, S., Srivatsa, A., Nahass, G. R., & Ajilore, O. (2023). AI Anxiety: A Comprehensive Analysis of Psychological Factors and Interventions. *Social Science Research Network*. https://doi.org/10.2139/ssrn.4573394

Komiak, S. Y., & Benbasat, I. (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS quarterly*, 941-960.

KNAW; NFU; NOW; TO2-Federation; Netherlands Association of Universities of Applied Sciences; VSNU (2018): Netherlands Code of Conduct for Research Integrity.

Krishnaraju, V., & Mathew, S. K. (2013). Web personalization research: an information system perspective. *Journal of Systems and Information Technology*, *15*(3), 254-268.

Kuntze, R., Wu, C. K., Wooldridge, B. R., & Whang, Y. (2019). Improving financial literacy in college of business students: modernizing delivery tools. *International Journal of Bank Marketing*, *37*(4), 976–990. https://doi.org/10.1108/ijbm-03-2018-0080

Lambillotte, L., Magrofuoco, N., Poncin, I., & Vanderdonckt, J. (2022a). Enhancing playful customer experience with personalization. *Journal Of Retailing And Consumer Services*, 68, 103017. https://doi.org/10.1016/j.jretconser.2022.103017

Lee, J. Y., & Huber, J. C. (2021). Evaluation of Multiple Imputation with Large Proportions of Missing Data: How Much Is Too Much? *Iranian journal of public health*. https://doi.org/10.18502/ijph.v50i7.6626

Lemke, F., Clark, M., & Wilson, H. (2011). Customer experience quality: an exploration in business and consumer contexts using repertory grid technique. *Journal of the academy of marketing science*, 39, 846-869.

Lemon, K. N., & Verhoef, P. C. (2016). Understanding Customer Experience Throughout the Customer Journey. *Journal Of Marketing*, 80(6), 69–96. https://doi.org/10.1509/jm.15.0420

Liang, Ting-Peng & Chen, Hsin-Yi & Turban, Efraim. (2009). Effect of personalization on the perceived usefulness of online customer services: A dual-core theory. *ACM International Conference Proceeding Series*, (279–288). https://doi.org/10.1145/1593254.1593296

Libai, B., Bart, Y., Gensler, S., Hofacker, C. F., Kaplan, A., Kötterheinrich, K., & Kroll, E. B. (2020). Brave New World? On AI and the Management of Customer Relationships. *Journal of Interactive Marketing*, *51*, 44–56. https://doi.org/10.1016/j.intmar.2020.04.002

Lim, W. M., Rasul, T., Kumar, S., & Ala, M. (2022). Past, present, and future of customer engagement. Journal of Business Research, 140, 439–458. https://doi.org/10.1016/j.jbusres.2021.11.014

Liu, J., Li, K., Yeh, S., & Chien, S. (2022). Assessing Perceptual Load and Cognitive Load by Fixation-Related Information of Eye Movements. *Sensors*, 22(3), 1187. https://doi.org/10.3390/s22031187

Lone, U. M., & Bhat, S. A. (2022). Impact of financial literacy on financial well-being: a mediational role of financial self-efficacy. *Journal Of Financial Services Marketing*. https://doi.org/10.1057/s41264-022-00183-8

Luna, B., Velanova, K., & Geier, C. F. (2008). Development of eye-movement control. *Brain and cognition,* 68(3), 293-308.

Lusardi, A., Hasler, A., & Yakoboski, P. (2020). Building up financial literacy and financial resilience. *Mind & Society*, 20(2), 181–187. https://doi.org/10.1007/s11299-020-00246-0

Lusardi, A., & Messy, F. (2023). The importance of financial literacy and its impact on financial wellbeing. *Journal Of Financial Literacy And Wellbeing*, *1*(1), 1–11. https://doi.org/10.1017/flw.2023.8

Makridakis, S. (2017). The forthcoming Artificial Intelligence (AI) revolution: Its impact on society and firms. *Futures*, 90, 46-60.

McLean, G., and Osei-Frimpong, K. (2019). Hey Alexa… examine the variables influencing the use of artificial intelligent in-home voice assistants. *Comput. Hum. Behav.* 99, 28–37. doi: https://doi.org/10.1016/j.chb.2019.05.009

Miller, J. G. (1978). Living systems. (pp. 147-167). New York: McGraw-Hill.

Molina, A. I., Arroyo, Y., Lacave, C., Redondo, M. Á., Bravo, C., & Ortega, M. (2024). Eye tracking-based evaluation of accessible and usable interactive systems: tool set of guidelines and methodological issues. *Universal Access in The Information Society*. https://doi.org/10.1007/s10209-023-01083-x

Morales, A. C., Amir, O., & Lee, L. (2017). Keeping It Real in Experimental Research—Understanding When, Where, and How to Enhance Realism and Measure Consumer Behavior. *Journal Of Consumer Research,* 44(2), 465–476. https://doi.org/10.1093/jcr/ucx048

Moreno, R., & Mayer, R. (2007). Interactive multimodal learning environments. *Educational Psychology Review*, *19*(3), 309–326. https://doi.org/10.1007/s10648-007-9047-2

Ng, D. T. K., Su, J., Leung, J. K. L., & Chu, S. (2023). Artificial intelligence (AI) literacy education in secondary schools: a review. *Interactive Learning Environments*, 1–21. https://doi.org/10.1080/10494820.2023.2255228

Nicolescu, L., & Tudorache, M. T. (2022). Human-Computer Interaction in Customer Service: The Experience with AI Chatbots—A Systematic Literature Review. *Electronics*, *11*(10), 1579. https://doi.org/10.3390/electronics11101579

Oberoi, P., Patel, C., & Haon, C. (2017). Technology sourcing for website personalization and social media marketing: A study of e-retailing industry. *Journal Of Business Research*, 80, 10–23. https://doi.org/10.1016/j.jbusres.2017.06.005

OECD/INFE, D'Agostino, F., & Karen, R. (2023). *OECD/INFE 2023 International Survey of Adult Financial Literacy* (C. Monticone & J. Huxley, Reds.).

Ouachani, S., Belhassine, O., & Kammoun, A. (2020). Measuring financial literacy: a literature review. *Managerial Finance,* 47(2), 266–281. https://doi.org/10.1108/mf-04-2019-0175

Perrig, S. A. C., Scharowski, N., & Brühlmann, F. (2023). Trust Issues with Trust Scales: Examining the psychometric quality of trust measures in the context of AI. *Conference On Human Factors in Computing Systems*. https://doi.org/10.1145/3544549.3585808

Philippas, N. D., & Avdoulas, C. (2021). Financial literacy and financial well-being among generation-Z university students: Evidence from Greece. In *Financial Literacy and Responsible Finance in the FinTech Era* (pp. 64-85). Routledge.

Phillips-Wren, G., & Adya, M. (2020). Decision making under stress: the role of information overload, time pressure, complexity, and uncertainty. *Journal Of Decision Systems*, *29*(sup1), 213–225. https://doi.org/10.1080/12460125.2020.1768680

Pillai, R., Sivathanu, B., & Dwivedi, Y. K. (2020). Shopping intention at AI-powered automated retail stores (AIPARS). *Journal of Retailing and Consumer Services*, *57*, 102207. https://doi.org/10.1016/j.jretconser.2020.102207

Polk, J., Tassin, C., & McNellis, J. (2020). Magic Quadrant for Personalization Engines. *Gartner Report Reprint*, 13.

Ringle, Christian M., Wende, Sven, & Becker, Jan-Michael. (2022). SmartPLS 4. Oststeinbek: SmartPLS. Retrieved from https://www.smartpls.com

Pupil Labs. (2024) Core [Computer software]. Retrieved from https://pupil-labs.com/products/core/tech-specs

Russell, S. J., Norvig, P., & Davis, E. (2010). *Artificial intelligence: A Modern Approach*. Prentice Hall.

Sainani, K. L. (2015). Dealing With Missing Data. Pm&r, 7(9), 990– 994. https://doi.org/10.1016/j.pmrj.2015.07.011

Salonen, V., & Karjaluoto, H. (2016). Web personalization: The state of the art and future avenues for research and practice. *Telematics And Informatics*, 33(4), 1088–1104. https://doi.org/10.1016/j.tele.2016.03.004

Salvucci, D. D., & Goldberg, J. F. (2000). Identifying fixations and saccades in eye-tracking protocols. https://doi.org/10.1145/355017.355028

Schmitt, B. (1999). Experiential Marketing. *Journal of Marketing Management*, 15(1–3), 53– 67. https://doi.org/10.1362/026725799784870496

Shah, N., Bhagat, N., Chauhan, H., & Shah, M. (2020). Research Trends on the Usage of Machine Learning and Artificial Intelligence in Advertising. *Augmented Human Research*, 5(1). https://doi.org/10.1007/s41133-020-00038-8

Shahpasandi, F., Zarei, A., & Nikabadi, M. S. (2020). Consumers' Impulse Buying Behavior on Instagram: Examining the Influence of Flow Experiences and Hedonic Browsing on Impulse Buying. *Journal Of Internet Commerce*, 19(4), 437–465. https://doi.org/10.1080/15332861.2020.1816324

Shafiee, S., Zhang, L. L., & Rasmussen, K. M. (2023). Improving financial literacy and supporting financial decisions: developing a personalized configurator. *Journal of the Knowledge Economy (Print)*. https://doi.org/10.1007/s13132-023-01651-9

Shan, L. H., Cheah, K. S. L., & Leong, S. (2023). Leading Generation Z's Financial Literacy Through

Financial Education: Contemporary Bibliometric and Content Analysis in China. *SAGE Open*, *13*(3). https://doi.org/10.1177/21582440231188308

Shin, D. (2020). User perceptions of algorithmic decisions in the Personalized AI System:Perceptual evaluation of fairness, accountability, transparency, and explainability. *Journal of Broadcasting & Electronic Media*, *64*(4), 541-565. https://doi.org/10.1080/08838151.2020.1843357

Steinfeld, A., Jenkins, O. C., & Scassellati, B. (2009). The oz of wizard. Human-Robot Interaction. https://doi.org/10.1145/1514095.1514115

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive science*, *12*(2), 257-285.

Tani, Y., Ishihara, R., Inoue, T. *et al.* (2023). A single-center prospective study evaluating the usefulness of artificial intelligence for the diagnosis of esophageal squamous cell carcinoma in a real-time setting. *BMC Gastroenterol* 23, 184. https://doi.org/10.1186/s12876-023-02788-2

Tyrväinen, O., Karjaluoto, H., & Saarijärvi, H. (2020). Personalization and hedonic motivation in creating customer experiences and loyalty in omnichannel retail. *Journal Of Retailing And Consumer Services*, 57, 102233. https://doi.org/10.1016/j.jretconser.2020.102233

Venkatesh, V., Morris, M. G., Davis, G. B. and Davis, F. D. 2003. User acceptance of information technology: Toward a unified view. MIS Quarterly. 27, 3 (2003), 425-478.

Voss, K. E., Spangenberg, E. R., & Grohmann, B. (2003). Measuring the Hedonic and Utilitarian Dimensions of Consumer Attitude. *Journal Of Marketing Research*, *40*(3), 310–320. https://doi.org/10.1509/jmkr.40.3.310.19238

Weijters, B., & Baumgartner, H. (2012). Misresponse to Reversed and Negated Items in Surveys: A Review. *Journal Of Marketing Research*, *49*(5), 737–747. https://doi.org/10.1509/jmr.11.0368

Wetzels, N., Odekerken-Schröder, N., & Van Oppen, N. (2009). Using PLS Path Modeling for Assessing Hierarchical Construct Models: Guidelines and Empirical Illustration. *Management Information Systems Quarterly*, *33*(1), 177. https://doi.org/10.2307/20650284

WHO. (2020). Coronavirus disease 2019 (COVID-19). *Situation Report* – 72. https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200401-sitrep-72-covid-19.pdf

Willis, V. (2024). The Role of Artificial Intelligence (AI) in Personalizing Online Learning. *Journal Of Online And Distance Learning*, *3*(1), 1–13. https://doi.org/10.47941/jodl.1689

Wong, T. P. & Guan, C. (2018). Personalisation in locationbased advertising: *The moderating effect of brand familiarity.* In Proceedings of the 18th International Conference on Electronic Business (pp. 447-460). ICEB, China

Wu, T., Chen, S., Yao, J., & Wu, P. (2020). Intelligent prognostic and health management based on

IOT cloud platform - *IEEE xplore*. Intelligent prognostic and health management based on IOT cloud platform. Retrieved January 17, 2023, from https://ieeexplore.ieee.org/abstract/document/9101690

Yuan, C., Zhang, C., & Wang, S. (2022). Social anxiety as a moderator in consumer willingness to accept AI assistants based on utilitarian and hedonic values. *Journal Of Retailing And Consumer Services*, *65*, 102878. https://doi.org/10.1016/j.jretconser.2021.102878

Zagermann, J., Pfeil, U., & Reiterer, H. (2016). Measuring cognitive load using eye tracking technology in visual computing. In *Novel Evaluation Methods for Visualization*. https://doi.org/10.1145/2993901.2993908

Zanker, M., Rook, L., & Jannach, D. (2019). Measuring the impact of online personalisation: Past, present and future. International *Journal Of Human-Computer Studies*, 131, 160–168. https://doi.org/10.1016/j.ijhcs.2019.06.006

Zhang, S., Meng, Z., Chen, B., Xia, Y., & Zhao, X. (2021). Motivation, social emotion, and the acceptance of artificial intelligence Virtual Assistants—Trust-Based Mediating effects. *Frontiers in Psychology*, *12*. https://doi.org/10.3389/fpsyg.2021.728495

Zhang, X., Guo, X., Guo, F., & Lai, K. (2014). Nonlinearities in personalization-privacy paradox in mHealth adoption: The mediating role of perceived usefulness and attitude. *Technology and Health Care*, *22*(4), 515–529. https://doi.org/10.3233/thc-140811

Appendices

Appendix 1. Operationalization table

Table 1. Operationalization table

Construct	Operationalization	Measure	Source
Cognitive load	- Fixation duration	Eye tracking	(Liu et al., 2022),
CE outcomes *Choice behavior*	- Number of flyers the participant takes - The type of flyer(s) the participant takes	Real time measure	(Morales et al., 2017).
AI usefulness	- The financial information I presented to you was useful - The financial information I presented to you was NOT helpful - The financial information I presented to you was practical	Seven point Likert-scale	(Hoffman et al, 2018; Perrig et al., 2023)
Control variables			
Age	- What is your age?		
Gender	- What gender are you identifying yourself with the most?	(1) Male (2) Female (3) Other (4) prefer not to say	
Faculty/study	- Which faculty are you studying at?	Faculty of Philosophy, Theology and Religious Studies, Faculty of Arts, Nijmegen School of Management, Faculty of Medical Sciences, Faculty of Science, Faculty of Law, Faculty of Social Sciences	(Radboud University, 2024)
English language	- What skill level is your English language	Seven point Likert-scale	
AI experience	- Have you been educated by an AI avatar before?	Yes, no, other	
Complexity	- The financial information I presented to you was complicated	Seven point Likert-scale	

Appendix 2. Consent form

Consent form

Purpose: This study aims to investigate the influence of personalization on customer experience and behavioral outcomes.

Equipment: Pupil Labs core eye-tracking, two laptops, three 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 response in terms of fixation durations 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 responsibly and correctly. 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 x (s…., 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

Appendix 3. Results Financial Literacy Topics Survey

Figure 1. Topics

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

Figure 2. Investing

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

Figure 3. Loans

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

Appendix 4. Prompts for AI

Appendix 4A: 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 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 must 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 examples, or apply their knowledge.

Appendix 4B: 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. Script 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.

<u>Script 2. Budgeting</u> (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.”

<u>Script 3. Investing</u> (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.

Same for both groups

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 6. AI-avatar

Figure 1. AI-avatar Mula

Figure 2. Mula Listening

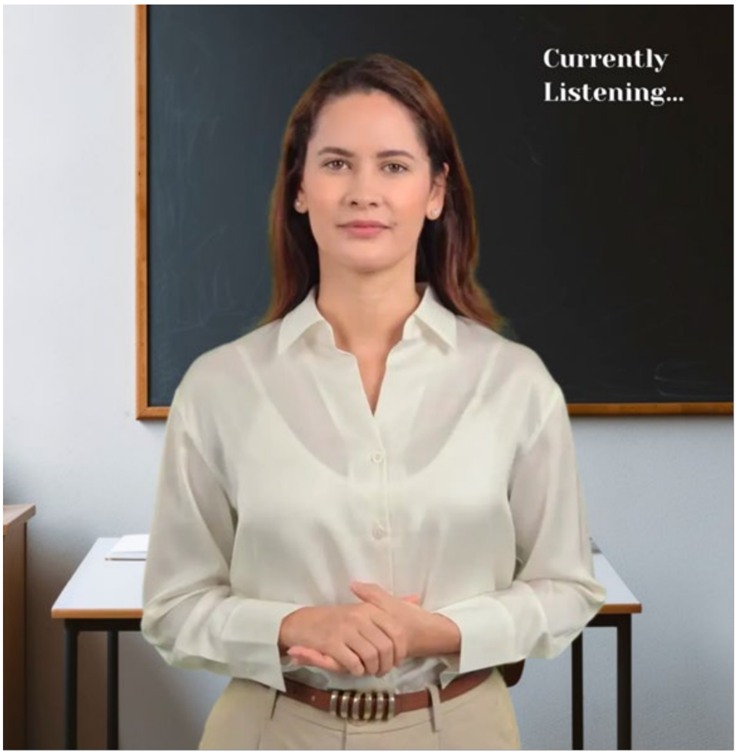
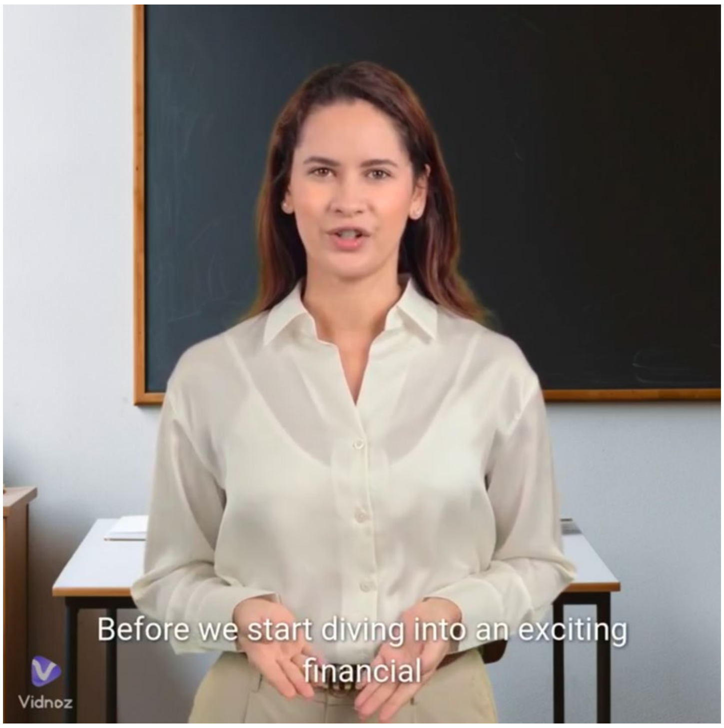


Figure 3. Mula Talking



Appendix 7. Flyers to measure behavior

Figure 1. Investing flyer

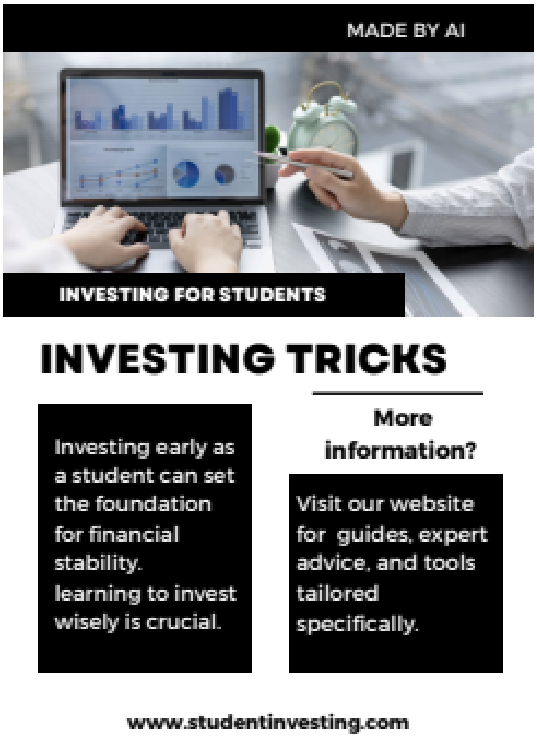


Figure 2. Budgeting flyer

Figure 3. Loans flyer

Appendix 8. Data cleaning SPSS

Table 1. 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 2. Little's MCAR test

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

Appendix 9. Results manipulation check pre-test

Table 1. KMO and Bartlett initial model

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 2. Communalities personalization

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 3. Component matrix personalization

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 4 Total variance explained personalization

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 5. Cronbach's Alpha

Reliability Statistics

Cronbach's Alpha	N of Items
,524	3

Table 6. Group Statistics

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 7. Independent Samples Test

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

Appendix 10. Results of the experiment check

Table 1. KMO and Bartlett's test

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 2. Communalities Matrix

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 3. 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 4. 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 5. Cronbach's Alpha

Reliability Statistics

Cronbach's Alpha	N of Items
,688	3

Table 6. Group statistics

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 7. Independent Samples Test

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 11. Evaluation of the model

Appendix 11A: Evaluation of measurement model

Table 1. Factor loadings

	Outer loadings
AIU_1 <- AIU	0.911
AIU_2_R <- AIU	0.864
AIU_3 <- AIU	0.579
Behavior_yes <- Behavior_yes	1.000
Complicated_Control <- Complicated	1.000
Fix_per_sec <- Fix_per_sec	1.000
LM_2_R <- LM	0.622
LM_3 <- LM	0.683
LM_4 <- LM	0.843
LM_5 <- LM	0.551
MANI_LM_1 <- LM	0.814
Male <- Male	1.000
Management <- Management	1.000
Personalized <- Personalized	1.000
englishskill <- English_skill	1.000

Table 2. Construct reliability

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
AIU	0.714	0.826	0.836	0.637
LM	0.753	0.812	0.833	0.506

Table 3. Discriminant validity

	AIU	Behavior_yes	Complicated	English_skill	Fix_per_sec	LM	Male	Management	Personalized
AIU									
Behavior_yes	0.249								
Complicated	0.302	0.080							
English_skill	0.052	0.082	0.062						
Fix_per_sec	0.093	0.107	0.201	0.029					
LM	0.678	0.315	0.287	0.124	0.250				
Male	0.044	0.303	0.078	0.246	0.032	0.125			
Management	0.152	0.206	0.055	0.110	0.159	0.219	0.047		
Personalized	0.526	0.164	0.170	0.230	0.016	0.309	0.076	0.094	

Table 4. Model fit

	Saturated model	Estimated model
SRMR	0.074	0.182
d_ULS	0.656	3.980
d_G	0.230	n/a
Chi-square	154.676	n/a
NFI	0.685	n/a

Table 5. Factor loadings, composite reliability, and average variance extracted of the constructs and their items

Component and manifest variables	Loading (t-value)
AIU	**CR: 0.836, AVE: 0.637**
Q1- The financial information I presented to you was useful	0.911 (48.024) *
Q2 - The financial information I presented to you was NOT helpful	0.864 (23.282) *
Q3 - The financial information I presented to you was practical	0.579 (6.206) *
LM	**CR: 0.833, AVE: 0.506**
Q1 - I am very interested in financial topics presented in this lesson	0.814 (23.640) *
Q2 - I do not enjoy learning about the financial concepts presented in this lesson (Reversed)	0.622 (5.957) *
Q3 - Understanding financial literacy is very important to me	0.683 (9.012) *
Q4 - The financial information provided in this lesson is important to me.	0.843 (24.887) *
Q5 - The financial literacy skills learned in this lesson will be valuable in other areas of my life.	0.551 (6.322) *
Notes: CR: Composite reliability; AVE: Average variance extracted, * $p < 0.01$	

Table 6. Correlations and square root of the AVE

Construct	1 AIU	2 LM
1 AIU	0.798	
2 LM	0.527	0.711
Notes: Values down the diagonal are the square roots of the AVE: all others are correlation coefficients.		

Table 7. GoF Index calculation

GoF Index calculation	
Mean construct communality	AIU (0.911*0.911) + (0.864*0.864) + (0.579*0.579)/3 = 0.63721293 Behavior = 1 Complicatedness = 1 English Skill = 1 Fix per sec = 1 LM (0.814*0.814) + (0.622*0.622) + (0.683*0.683) + (0.843*0.843) + (0.551*0.551) /5 = 0.5060438 Male = 1 Management = 1 Personalization = 1 **Mean construct communality:** 0.63721293+1+1+1+1+0.4975478+1+1+1= 8.14325673 8.14325673/9= 0.9048063033
Mean adjusted- R^2	0.224 + 0.101 - 0.008 + .325 = 0.642 0.642/ 4 = 0,1605
Mean construct communality x R^2	0.9048063033* 0,1605 = 0.1452214117
GoF Index	√ 0.1452214117 = 0.38107992722

Appendix 11B: Evaluation of the structural model

Table 1. VIF values among constructs

	AIU	**Behavior_yes**	**Complicated**	**English_skill**	**Fix_per_sec**	**LM**	**Male**	**Management**	**Personalized**
AIU		1.460				1.460			
Behavior_yes									
Complicated		1.124				1.124			
English_skill		1.187				1.187			
Fix_per_sec	1.000	1.077				1.077			
LM									
Male		1.102				1.102			
Management		1.089				1.089			

Personalized	1.000	1.502			1.000	1.502			

Table 2. Adjusted R^2 values of the constructs

	R-square	**R-square adjusted**
AIU	0.239	0.226
Behavior_yes	0.205	0.154
Fix_per_sec	0.000	-0.008
LM	0.367	0.326

Table 3. Effect sizes (f2)

	AIU	**Behavior_yes**	**Complicated**	**English_skill**	**Fix_per_sec**	**LM**	**Male**	**Management**	**Personalized**
AIU		0.018				0.247			
Behavior_yes									
Complicated		0.000				0.011			
English_skill		0.000				0.013			
Fix_per_sec	0.000	0.021				0.047			
LM									
Male		0.105				0.015			
Management		0.049				0.016			
Personalized	0.314	0.016			0.000	0.002			

Table 4. Path coefficients

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
AIU -> Behavior_yes	0.064	0.064	0.045	1.413	0.158
AIU -> LM	0.478	0.479	0.090	5.334	0.000
Complicated -> Behavior_yes	-0.007	-0.007	0.039	0.171	0.864
Complicated -> LM	-0.089	-0.092	0.081	1.093	0.275
English_skill -> Behavior_yes	-0.000	-0.001	0.039	0.006	0.995
English_skill -> LM	0.099	0.096	0.083	1.200	0.230
Fix_per_sec -> AIU	0.008	0.007	0.084	0.097	0.923
Fix_per_sec -> Behavior_yes	0.060	0.061	0.035	1.733	0.083

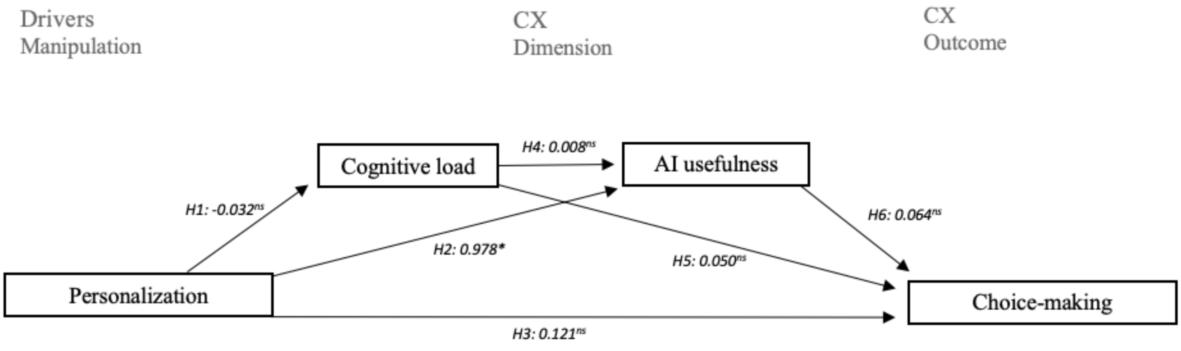
Fix_per_sec -> LM	-0.180	-0.178	0.076	2.375	0.018
Male -> Behavior_yes	0.273	0.274	0.079	3.442	0.001
Male -> LM	0.207	0.218	0.165	1.254	0.210
Management -> Behavior_yes	0.185	0.184	0.073	2.529	0.011
Management -> LM	0.213	0.213	0.173	1.231	0.218
Personalized -> AIU	0.978	0.996	0.133	7.330	0.000
Personalized -> Behavior_yes	0.121	0.122	0.089	1.362	0.173
Personalized -> Fix_per_sec	-0.032	-0.035	0.184	0.172	0.864
Personalized -> LM	0.084	0.102	0.198	0.425	0.671

Table 5. Serial mediations effects

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Personalized -> Fix_per_sec -> AIU	-0.000	-0.004	0.017	0.015	0.988
Personalized -> Fix_per_sec -> AIU -> LM	-0.000	-0.002	0.008	0.015	0.988
Fix_per_sec -> AIU -> Behavior_yes	0.001	-0.000	0.007	0.077	0.939
Personalized -> Fix_per_sec -> Behavior_yes	-0.002	-0.001	0.013	0.150	0.881
Fix_per_sec -> AIU -> LM	0.004	0.002	0.041	0.095	0.925
Personalized -> AIU -> Behavior_yes	0.063	0.064	0.047	1.344	0.179
Personalized -> Fix_per_sec -> LM	0.006	0.004	0.036	0.160	0.873
Personalized -> AIU -> LM	0.467	0.476	0.109	4.307	0.000
Personalized -> Fix_per_sec -> AIU -> Behavior_yes	-0.000	-0.000	0.001	0.012	0.990

Appendix 11C. Results of the hypotheses

Figure 1. Hypotheses outcomes



* Meets or exceeds p< 0.01 (two-tailed), ns: non-significant

Appendix 11D: Visual representation of the model

Figure 1. Visual representation of the model in SmartPLS