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“O Homem é do tamanho do seu sonho”

Fernando Pessoa

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Resumo

À medida que o uso de Inteligência Artificial (IA) cresce, aumentam também as questões sobre esta nova tecnologia e os seus potenciais usos. Entre as várias possibilidades e utilizações que poderiam ser oferecidos pela IA está a tecnologia de personalização de notícias, a qual poderia ser uma alternativa interessante para as plataformas de *streaming* de vídeo *over-the-top* (OTT). Considerando esse contexto, o propósito da presente investigação é avaliar os níveis de confiança que os utilizadores teriam em notícias de vídeo personalizadas geradas por IA. Para isso, uma amostra de 306 respondentes foi convidada a participar numa experiência *online*. Do total de participantes, 152 estiveram aleatoriamente sujeitos a um vídeo gerado por IA e a uma descrição sobre a tecnologia de personalização de notícias. Os restantes 154 respondentes assistiram ao mesmo vídeo exibido por um apresentador humano sem menções sobre personalização. Uma análise PLS-SEM foi usada para testar todas as sete hipóteses desta pesquisa. Os resultados revelaram níveis de confiança similares entre aqueles que assistiram notícias personalizadas geradas por IA e aqueles que assistiram ao apresentador humano. No entanto, o estudo também manifestou efeitos não significativos entre a riqueza de informação e a atração social na utilidade percebida pelos utilizadores. Do mesmo modo, o impacto da perceção da facilidade de uso da tecnologia na confiança dos usuários também foi irrelevante. A principal conclusão desta investigação foi que o conteúdo gerado por IA, nomeadamente a personalização de notícias de vídeo, pode ser potencialmente digno de confiança para utilizadores.

Palavras-chave: inteligência artificial; notícias personalizadas; confiança; OTT; TAM.
Sistema de classificação JEL: M16 – Administração Internacional de Negócios; M31 – Marketing.

Abstract

As the use of artificial intelligence (AI) grows, so do the questions regarding this new technology and its potential uses. Among the various possibilities and employments that could be offered by AI is personalized news technology, which could be an interesting alternative in over-the-top (OTT) video streaming platforms. Considering this context, the purpose of the present investigation is to assess the levels of trust that users would have in AI-generated personalized video news. For that, a sample of 306 respondents was asked to participate in an online experiment. Out of the total respondents, 152 were randomly assigned to an AI-generated news video and a description of the personalized news technology. The remaining 154 watched the same video presented by a human presenter, with no mention of personalization. A PLS-SEM analysis was used to test all seven hypotheses of this research. The results reveal similar levels of trust among those who watched AI-generated personalized news and those who watched the human presenter. Yet, the study also manifested non-significant effects of media richness and social attraction on the users' perceived usefulness. Likewise, the impact of perceived ease of use of the technology on users' trust was also irrelevant. The main conclusion of this investigation is that AI-generated content, namely personalized video news, can be potentially trustworthy for users.

Keywords: artificial intelligence; personalized news; trust; OTT; TAM.
JEL classification system: M16 – International Business Administration; M31 – Marketing.

Table of Contents

Glossary

Artificial intelligence – AI

Attitude towards using the system – A

Average variance extracted – AVE

Behavioral intention to use – BI

Body of European Regulators for Electronic Communications – BEREC

Common method variance – CMV

Composite reliability – CR

Covariance-based structural equation modeling – CB-SEM

Heterotrait-monotrait – HTMT

Marker variable – MV

Media richness – MR

Over-the-top – OTT

Partial least squares structural equation modeling – PLS-SEM

Perceived intelligence – PI

Social attraction – SA

Standardized root mean square residual – SRMR

Theory acceptance model – TAM

Theory acceptance model 2 – TAM 2

Theory acceptance model 3 – TAM 3

Theory of reasoned action – TRA

Trust – T

Unified theory of acceptance and use of technology – UTAUT

Unified theory of acceptance and use of technology 2 – UTAUT 2

Variance inflation factor – VIF

CHAPTER 1

Introduction

Technology is reshaping and transforming different business environments, particularly the service ecosystem (Huang & Rust, 2017; Peltier et al., 2020). Businesses are continuously adopting, adapting, and implementing new technologies in their activities (Renko & Druzijanic, 2014). At the same time, customers are experiencing these new technologies and developing either favorable or unfavorable tendencies that help to draw paths toward innovative discoveries (Adapa et al., 2020). Since the 2000s, the Internet and the Web have facilitated the obtention of data, representing a new dimension in understanding customers and sketching new business opportunities (Chen et al., 2017). The combination of these elements generates a dynamic innovative context both for companies that seek business opportunities and for customers.

This innovative context has enabled customer participation in the development of co-created value, in which companies and customers collaborate to create value for innovation under a service-dominant logic (Peltier et al., 2020; Vargo & Lusch, 2016). The concept of co-creation already existed in other disciplines before the 21st century (Ranjan & Read, 2016); however, it only became noticeable in marketing research after the 2000s, based on studies by Prahalad and Ramaswamy (2000). Companies such as Google, Amazon, and Netflix are a few examples of organizations that use technology to provide personalized services to their clients (Alimamy & Gnoth, 2022). User participation in business has become an essential feature of services in Web 3.0. For instance, Netflix has a recommender system that influences about 80% of streamed hours, while the remaining 20% results from a user search that is made with another type of algorithm (Gomez-Uribe & Hunt, 2015). Mechanisms like the one offered by Netflix can deliver a unique experience to each customer according to the user's preferences and choices.

The universe of online news has also experienced opportunities for growth and change. The concept of personalized news has gained relevance, as newspapers, broadcasters, websites, social media, and applications are allowing users to personalize the information they receive. This alternative to news consumption is not limited to online platforms: Traditional players in the news industry have also developed this technology, including, for instance, the BBC (Thurman, 2011) and The New York Times (Spayd, 2017). The main idea behind the personalization of news is an effective recommender system, based on algorithms capable of understanding users' tastes and interests, which selects and recommends content (Kwak et al., 2021; Lin et al., 2014; Thurman et al., 2019). This system would reduce the friction that readers experience searching for the news that they are most interested in, improving user experience (Møller, 2022).

The main enabler of personalized news technology is artificial intelligence (AI). The online personalization of news on a large scale would not be possible without AI. Today, it is already possible to produce journalistic content through AI (Anderson, 2013; Carlson, 2014; Graefe & Haim, 2017). Digital storytelling has become a reality through automated journalism powered by AI (Caswell & Dörr, 2018; Galily, 2018; Linden, 2017; Thorne, 2020). According to the definition, “Artificial intelligence applies advanced analysis and logic-based techniques, including machine learning, to interpret events, support and automate decisions, and take actions” (Gartner Group, 2019). Different from other automated technologies, AI can receive, process, and interpret data to make decisions. In personalized news technology, algorithms are responsible for selecting content and sorting it according to the personalization criteria (Powers, 2017).

So far, AI has been studied in different fields with distinct research focuses. In management, researchers tend to look at the impacts of AI on businesses and their various stakeholders. In computer science, investigations normally examine deep-learning algorithms and their mechanisms. Finally, in the social sciences, research usually leans toward the ethical and legal dimensions of AI (Loureiro et al., 2020). Nevertheless, because AI technology is still under constant development, further research is needed. Studies of news-personalization technologies have mainly focused on research engines and filtering mechanisms (Darvishy et al., 2020; Haim et al., 2017; Lin et al., 2014; Manoharan & Senthilkumar, 2020; Wang, 2019; Wieland et al., 2021). Yet, few studies examine news aggregators (Haim et al., 2019; Kwak et al., 2021) and, most importantly, the effects of news personalization on audiences (Merten, 2021; Swart, 2021; Thurman et al., 2019), thus demanding further research. Although AI-generated news articles already exist, AI-generated video news is still emerging as a technology for the future (Wang et al., 2022). AI is an imminent reality for the future, reshaping the news media (Brennen et al., 2022; Linden, 2017; Thorne, 2020). Hence, it is still necessary to investigate the impacts that this technology potentially offers to users.

Therefore, the current investigation seeks to respond to this need to deepen research into the area of news personalization through AI, in particular by analyzing the response of audiences toward current and future technological tendencies.

As AI technology evolves, there is a propensity to increase the degree of AI use in over-the-top (OTT) services, particularly in OTT video streaming services. This was the starting point of the present research: understanding that AI-generated personalized news technology may be significantly present in OTT video streaming services in a near future.

According to the Body of European Regulators for Electronic Communications (BEREC), an OTT service is defined as “content, a service or an application that is provided to the end-user over the public Internet” (BEREC, 2016, p. 3). These services include content (media), messages, physical services, video content, and even games. In 2020, more than 26% of Americans got news from YouTube, one of the world’s largest OTT video streaming platforms (Stocking et al., 2021). Between 2022 and 2027, newspapers and magazines (print and online) should feel a decrease in revenue of US$ -9.2 billion (Statista, 2022a), while OTT platforms should experience an increase in revenue of US$ 201,44 billion (Statista, 2022b). These figures are just a tiny snip of potential changes in the media and news industry.

Taking into consideration the current evolution of technology and the possibility of having news programs entirely generated by AI, the main aim of this research is to investigate the levels of trust that users have in AI-generated personalized video news. In other words, the investigation aims to answer the following question: Would users trust AI-personalized video news to the same extent they trust human-generated video news?

This investigation concludes that three objectives must be considered and associated with the research question:

1) To define trust within the context of this research and based on recent literature.
2) To develop a conceptual model capable of identifying the main variables that influence trust.
3) To compare levels of trust among those who have experienced AI-generated personalized video news and those who have watched human-generated video news.

To achieve the research's aim and objectives, this paper is divided into five different sections. The first is the Literature review, which intends to revise the main publications on the subject, highlighting key concepts, theories, and terminologies. Based on the literature, seven hypotheses and a conceptual model are designed to serve as the theoretical framework of this research. The second section is the Research methodology, where the methodology is explained in greater detail. The third section is the Data analysis, which presents and examines the results obtained from the experiment. The fourth section is the Discussion, where the evaluation and interpretation of results are presented. The fifth and final section of this investigation is the Conclusion, with the main considerations of the research.

In terms of contributions, this research has at least two main implications. Firstly, for practitioners, this investigation can offer ideas, insights, evaluations, and conclusions regarding a potential technology for personalizing video news. Companies, private entities, and institutions can take advantage of this paper by exploring the opportunities, benefits, and potential areas of growth that this technology has to offer. Secondly, to academia, this paper contributes a unique study about the technology of personalizing video news. Both its results and its conceptual model can be extended and used with distinct approaches.

CHAPTER 2

Literature review

The purpose of this section is to convey the most relevant theories and discussions on the topic of this research. The literature review also aims to present an overview of the main definitions, ideas, and positions regarding the analyzed topic. Therefore, this section starts with the basic concepts of the topic, going through the key terms and their definitions, and the section ends by approaching the specificities of this subject.

2.1. Over-the-top services

The technological development of the Internet brought with it a new concept to define the possibility of consuming services that are available over the Internet: OTT services.

Among these services are music streaming, communication networks, and video streaming, which is certainly the most popular and dominant OTT service nowadays (Martínez-Sánchez et al., 2021). In figures, the number of OTT video users in 2017 was equivalent to 2.20 billion, while in 2021, it reached 3.34 billion users (Statista, 2022b). Within less than 4 years, the number of users grew by almost 52%, and predictions for 2027 indicate that the total number of users can increase to a total of 4.22 billion (Statista, 2022b). Additionally, revenues from the OTT video market show significant margins of growth: The revenue projection of US$275.30 billion for 2022 is expected to increase to US$476.60 billion within 5 years, which means an annual growth rate of almost 12% within that period (Statista, 2022b).

2.1.1. The impact of technology on business

Television has been the basis of media consumption for decades (Malthouse et al., 2018). It is considered a medium or a portal for distribution technologies, including broadcast signals and cable wires (Lotz, 2017). However, the introduction and subsequent development of OTT platforms have brought structural changes to the entertainment industry.

The essence of these changes is proposed by media scholar Amanda Lotz (2007, p. 3), with the “push” and “pull” effects that technologies have on audiences. Audiences are always active in their interactions with video content; they are not passive at all (Aguirre et al., 2016; Hermida et al., 2012; Hu et al., 2017). Even with traditional television broadcasters, audiences exchange information, ideas, and opinions in collective groups (Hu et al., 2017). Nevertheless, as technology evolved, so did both the access to information and the forms of media consumption (Napoli, 2010). Before the postmodern era, media content was imposed through a “push” technology, in which content providers had power over what would be broadcast to customers through television. The broadcast distribution with television schedules helps illustrate the idea of having a distributor and receptors (Lobato, 2018). In contrast, the postmodern era is characterized by the “pull” technology, through which customers have power over what content they consume, when they consume it, and in which medium they consume it.

The effectiveness of OTT video streaming platforms among audiences is directly related to suitable usage and accessibility (Yousaf et al., 2021). This suggests that even platforms that operate under the subscription model can be very attractive due to their low and competitive prices (Jung & Melguizo, 2022). Nevertheless, streaming platforms have also moved beyond convenience, betting on content production. This strategic step has put significant pressure on traditional players in the video industry, which used to dominate content production (Afilipoaie et al., 2021). OTT video streaming platforms have become transnational broadcasters, disrupting the national/local power that broadcasters have (Jenner, 2018, p.185).

Consequently, traditional media industries have been experiencing a significant disruption caused by on-demand video-streaming platforms (Martínez-Sánchez et al., 2021; McKenzie et al., 2019). Over the past half-decade, OTT video streaming services have shown the potential power to act as a substitute for paid television (Jung & Melguizo, 2022).

Nowadays, with expanded Internet coverage and a huge variety of devices that support OTT video streaming, the video industry has been redesigned. Technology is shaping audiences and societies, creating an “on-demand culture” of personalized experiences (Tyron, 2013, p. 117-135). With on-demand services, users are able to have individualized experiences according to their tastes and preferences. Personalization has become a key asset for promoting unique user experiences.

2.2. Personalization of news

Personalization can be described as the practice of adapting products/services for the customer according to the information available and based on his or her exclusive preferences (Li, 2016; Montgomery & Smith, 2009). Personalization is about delivering the right product/service to the right customer at the right time so as to captivate new business opportunities, creating a link between customer and marketeer (Kumar et al., 2019; Tam & Ho, 2006). In personalization, the company actively decides on the marketing mix (Aguirre et al., 2015). The main aim of personalization is to create benefits for customers, hence generating customer satisfaction through an enhanced user experience (Gutierrez et al., 2019; Vesanen, 2007).

The combination of technology developments, data availability, and digital consumers has produced a competitive environment in which online experience plays an important role (Riegger et al., 2020). In this context, personalization becomes a key factor that has been adopted in various industries, including the news media.

Today, due to the large availability of content, news consumers have an overload problem (Li & Wang, 2019; Manoharan & Senthilkumar, 2020): Considering the large variety of mediums and sources, it is more difficult to find relevant information (Nanas et al., 2010; Powers, 2017). The solution to the overload problem arrives through personalization technology, which allows exclusive access to information that is tailored according to the user's preferences (Beam & Kosicki, 2014). Digital transformation is shifting media consumption patterns, allowing the development of personalized news through OTT services and websites (Bengtsson & Johansson, 2021). Based on news segmentation, personalized news enables customers to directly access topics of their interest, selecting favorable or preferred news (Dong & Lian, 2012; Haim et al., 2017; Thurman et al., 2019) and decreasing both the search effort and the costs of processing information (Chung et al., 2016). News consumers have gained power over producers as user interaction with news producers increases (Fletcher & Park, 2017). With personalization, consumers can tailor information to their personal preferences and activities, enhancing their experience (Kormelink & Meijer, 2014).

Personalization can be an effective element in an interactive marketing strategy to enhance customer experience, but depending on the context, it can also be extremely ineffective (Aguirre et al., 2015; Huang & Rust, 2020). At least two points can influence the effectiveness of a marketing strategy that adopts personalization. The first one is related to the technological resources that a company holds as personalization is expensive requiring data and technology to be implemented (Arora et al., 2008). Companies need to have access to information to deliver products/services to customers; however, that information is expensive. Technology has been a primary enabler for companies to access customers' information (Montgomery & Smith, 2009), but costs are still considered to be high. Secondly, the concern of invasion of privacy through data collection can trigger customer dissatisfaction, including the fear of filter bubbles (Arora et al., 2008; Gutierrez et al., 2019). Companies need to comprehend the expected borders of privacy and design tailored products/services respecting those limits. From the moment this limit is exceeded, customer satisfaction is at stake, consequently threatening customer value.

A direct consequence of the increased use of data for personalization is customers' increasing awareness of information usage. The personalization paradox describes the potentially negative impacts that data collection for personalization can have on customers. Those who value information transparency are less likely to participate in online personalized experiences (Awad & Krishnan, 2006; Gutierrez et al., 2019). In general, companies can collect data in two ways: through overt data collection, in which the customer is aware of the fact that their data are being collected, and through covert data collection, a strategy in which marketers conceal the process of data collection from customers (Aguirre et al., 2016). Depending on the exposition of the collected data, covert data collection can generate negative impacts on customer experience (Gutierrez et al., 2019; Milne et al., 2000).

In the universe of personalized news, data collection is a crucial point, given that any form of news personalization relies on it. In general, there are at least two main forms of collecting data in what is known as computational journalism (Diakopoulos & Koliska, 2017): self-selection personalization and pre-selected personalization. The former is driven by the user's indication of exclusive content they are willing to access (Borgesius et al., 2016). In this approach to data collection, the users are accountable for indicating the kind of content they want to receive (Wang & Shang, 2016). The second form of data collection is through pre-selected personalization, which is driven by content providers, without the user's input (Borgesius et al., 2016; Haim et al., 2017). The idea behind pre-selected personalization is that personalization cannot be entirely based on the user's disclosed interests (Sela et al., 2015). Depending on the type of filtering, the pre-selected personalization can be subdivided into two. The content-based filtering assesses content according to the user's evaluation of incoming information (Møller, 2022; Nanas et al., 2010). This approach builds profiles by analyzing previously accessed and favored content and recommends new information following the profile's characteristics (Wang & Shang, 2016). In contrast, collaborative filtering evaluates content according to the opinion of the community members, that is, information and content that are external to the user's profile (Li & Wang, 2019; Møller, 2022; Nanas et al., 2010). Instead of considering content items as content-based filtering, collaborative filtering considers the opinions of different users to generate recommendations (Wang & Shang, 2016). Despite their differences, both data collection models intend to solve the information overload problem by delivering personalized content.

Notwithstanding, another problem arises with the practice of personalizing news: the fear of filter bubbles. The concept of filter bubble or information cocoon labels the restricted diversity of content/information that users can be exposed to by using systems of personalized news (Borgesius et al., 2016: Nechushtai & Lewis, 2019; Parisier, 2011; Powers, 2017). The personalization of news can trigger a fear of missing out on important information audiences, and this apprehension may have an impact on technology acceptance (Thurman et al., 2019). The fear of filter bubbles is directly linked to a potential lack of diversity of information that personalized news may impose on users, and the main question here is how far the boundaries of personalization should extend (Haim et al., 2018; Kunert & Thurman, 2019).

Although recent, the concept of online personalized news still has a significant margin of growth. The overload problem, which is potentialized by the vast diversity of news outlets, is still a significant issue for news consumers (Li & Wang, 2019; Manoharan & Senthilkumar, 2020). Again, personalized news technology tends to be an interesting solution to this issue. However, the key element of this solution lies in its personalization technology through OTT services and websites, translated into the capacity of delivering the expected content. In this context, AI is crucial in online personalization. Its contribution is decisive in processing data provided by customers and acting as a news gatekeeper (Haim et al., 2018; Møller, 2022; Nechushtai & Lewis, 2019; Powers, 2017).

2.3. Artificial intelligence

Artificial intelligence has played a big role in allowing the current stage of the development of personalized news. The world is currently experiencing what is considered the Fourth Industrial Revolution, with a strong tendency toward integrating the physical/biological worlds with the digital world (Schwab et al., 2018, p. 7). The main feature of this transformation is the introduction of disruptive technologies that connect the real and the virtual spheres. AI is a very important tool in this context.

Artificial Intelligence can be defined as a system capable of thinking humanly, acting humanly, thinking rationally, or acting rationally (Russell & Norvig, 2010, p. 2; Tussyadiah, 2020). In other words, it is a system that tries to replicate human cognitive thinking, transforming information and data into actions autonomously (Huang et al., 2022b).

Hung and Rust (2018) suggest that AI can be classified into four different kinds of intelligence, according to their capabilities of replicating human skills: mechanical, analytical, intuitive, and empathetic intelligences. Analytical intelligence, which is the most widespread type of intelligence, is already sufficient to provide mass personalization through big data. Despite the technological developments, AI is still very task-automated, with standardized applications based on a set of rules. Context awareness (intuitive intelligence), the form of intelligence that provides context-specific responses, is still to be developed (Davenport et al., 2020). It is a strong AI due to the ability to learn intuitively from experience (Huang & Rust, 2018). It is expected that technology will be able to develop to intuitive intelligence, which service robots could use to provide similar interactions to those of humans (Wirtz et al., 2018).

So far, the analytical intelligence provided by AI has been developed by companies to provide customized/personalized experiences for users through deliberate and pragmatic learning (Marinova et al, 2016). In the universe of OTT video streaming services, Netflix, for instance, became famous due to its 2006 Netflix Prize contest for developing a more accurate recommending system than the company initially had (Feuerverger et al., 2012; Hallinan & Striphas, 2016). The video streaming platform has a combination of algorithms that work together to provide the Netflix experience to users (Gomez-Uribe & Hunt, 2015).

Because AI-powered recommender systems are still not the core business of the news industry, news companies are experimenting with recommender systems to provide personalized news to their customers (Thurman et al., 2019). So far, organizations that offer personalized news recommendations have been using three methods of recommendation: pure content-based recommendation; collaborative filtering; and hybrid methods, which combine the first two (Darvishy et al, 2020; Lin et al., 2014; Li & Wang, 2019; Møller, 2022). This learning process takes place through cognition and user behavior (Chan et al., 2021). Therefore, the use of AI in personalized news still has considerable margins of growth.

Personalized news is offered as OTT services in at least three different formats: written, audio, and video. Applications that are exclusively dedicated to delivering personalized news are available in both written and video news formats, including, for instance, Google News, BBC News, and Flipboard, among others. Some OTT streaming platforms also provide news broadcasts through news channels. Spotify, for example, presents channels with recorded audio news. Similarly, YouTube hosts channels with both live video-streaming broadcasts and video-recorded news. All these OTT platforms rely on

AI to generate personalized content through recommendations that work as news gatekeepers (Haim et al., 2018; Møller, 2022; Nechushtai & Lewis, 2019; Powers, 2017).

The continuous development of AI has raised many concerns and expectations regarding the potential uses of strong AI, that is, AI that replicates human intuitive intelligence (Brennen et al., 2022). Automated journalism or computational journalism are already used to refer to the use of algorithms and data to produce journalistic content (Anderson, 2013; Caswell & Dörr, 2018; Carlson, 2014; Galily, 2018; Graefe & Haim, 2017; Linden, 2017; Thorne, 2020). While AI-generated stories already exist and have been used by media companies like Forbes (Graefe et al., 2018), AI-generated video content is still in the early stage of development (Wang et al., 2022). In the news world, however, the use of AI-generated content is already a reality and is tending toward being expanded (Graefe et al., 2018; Linden, 2017; Thorne, 2020). OTT video streaming platforms could be a fertile ground for the development of AI-generated video news, particularly personalized news.

Among the different variables capable of influencing users' perception of an AI technology, perceived intelligence would be determinant in AI-generated video news considering the transmission of information. As in any parasocial interaction, perceptions of intellectual capability can impact the user's perception of the technology. Hence, the perceived intelligence of an AI technology should be taken into consideration in the analysis of perceptions that audiences can have of technology.

2.4. Perceived intelligence

One of the most noticeable features of AI technology is perceived intelligence (Lee & Chen, 2022). Because technologies use intelligence to complete tasks and solve complex problems, perceived intelligence is understood as the perception of efficient behavior on the part of the technology, capable of delivering effective outputs (Moussawi et al., 2021). Traditionally, perceived intelligence is measured according to the perceived competency of the technology (Bartneck et al., 2009). The perception of intelligence in technology takes place when users notice knowledge, intelligence, and/or purpose in the technology (Johnson et al., 2009). Therefore, the concept of perceived intelligence is directly linked to the human perception of the capacity that technology has to offer.

Perceived intelligence also tends to be tied to the extent to which technologies can imitate human intelligence (Quiu et al., 2020). However, perceived intelligence should not be confused with perceived anthropomorphism, which is the representation of human characteristics that technology has (Aw et al., 2022). In AI technologies, perceived intelligence and perceived anthropomorphism are related and classified as AI features (Lee & Chen, 2022). McLean et al. (2021) classify perceived intelligence as one social attribute of AI technology, alongside social attraction. In summary, perceptions of intelligence in technology may work as a powerful stimulus capable of influencing the user's intention to use (Balakrishnan et al., 2022; Balakrishnan & Dwivedi, 2021a; Chuach et al., 2021; Lee & Chen, 2022). Hence, perceived intelligence may play a determinant role in AI technology.

Although perceived intelligence is determinant in the user's understanding of an effective behavior of the technology, it is not sufficient to comprehend an AI-generated technology's main attributes: Besides perceived intelligence, the sense of human presence is also important whenever considering any interaction that does not take place in person. Therefore, to capture the most essential human attributes in an interaction, it is inevitable to consider the notions of social presence, more precisely, social attraction.

2.5. Social attraction

Social attraction is a construct derived from social presence. Social presence is defined as the extent to which the medium enables users to sense that other users are psychologically present to them (Hassanein & Head, 2006). In a simplified way, it could be the sensation of being together with others (Huang et al., 2022a). In journalism, social presence is felt as "the sense of a human behind the news" (Marchionni, 2014, p. 232). The definitions of social presence recall the social presence theory of Short et al. (1976), which was one of the early studies to recognize and evaluate the degree of psychological perception of proximity that different mediums could have. Nowadays, the concept of social presence as a construct has become a key component in social networks (Zhao et al., 2018). Alternatively, social presence could be also referred to as parasocial interaction, a term from the 1950s that highlights the relationship between media users and the media (Hsieh & Lee, 2021; Xiang et al., 2016).

Over the years, social presence has been adopted and used in studies as a construct capable of measuring the emotive reactions users express using technologies (Zhao et al., 2018). There are at least three types of human presence: physical (the notion of being physically based in any virtual medium), social (the experience of social interactions with non-human intelligence), and self-presence (a state in which the virtual self is perceived as the actual self; Lee, 2004). Among these three types, social presence is the one with the most implications regarding human-robot interactions due to the generation of feelings capable of influencing customer behaviors (Lee et al., 2006; Wirtz et al., 2018). Likewise, AI computers have developed a strong sense of social presence by reproducing reciprocal interactions with humans. These AI-based interactions convey perceptions of social presence through social attraction (McLean et al., 2021). Compared to social presence, social attraction means having a positive feeling or attitude toward others (Huang et al., 2022a). In practice, while social attraction examines the psychological sensation of proximity, social attraction goes one step further by analyzing the presence (or lack of) positive appeal in the interaction.

Social presence and media richness are considered to be related concepts (Hassanein & Head, 2006). As users interact with AI technologies, looking for convenience and efficiency, rich media and perceived presence work together as stimuli for engagement (McLean et al., 2021). Social presence and social attraction rely on rich information to generate a sufficient impact on users. Similarly, the richness of media depends on the way information is displayed by the medium. Information is key in any interaction, including parasocial interactions. Therefore, it is possible to argue that media richness is a determinant of social presence (Walter et al., 2015). Together, social presence and media richness determine the degree of relationship users may have with the media.

2.6. Media richness

Media richness theory (Daft & Lengel, 1984; 1986) analyzes the flow of information processing in organizations within the scope of a descriptive model. Media richness, or information richness, is defined as "the ability of information to change understanding within a time interval" (Daft & Lengel, 1986, p. 560). The concept assumes that information (media) can vary and change the understanding of those who receive it (Wang et al., 2012). That is, information receivers can have different perceptions of information depending on the medium, which determines the way they receive information. The key aspect of the theory is the combination between ambiguity and the communication medium (Cho et al., 2009).

According to the theory, two forces influence information processing: uncertainty and equivocality. The first, uncertainty, represents the lack of information, while the second, equivocality, means the existence of conflicting or contradicting information. Organizations should be structured in such a way that the amount of information is useful and easy to acquire, reducing uncertainty. In addition, information should be rich and clear, avoiding equivocality (Daft & Lengel, 1986). By applying media richness theory to the digital world, communications with a high degree of media richness tend to reduce uncertainty and equivocality, increasing user interactions effectively (Chang & Yang, 2013). Thus, media richness can play a determinant role in digital technologies.

Over the years, as technology has evolved, so has the possibility of delivering rich information. On the one hand, lean media (e.g., written text) is more effective in comparison to rich media (e.g., video) in the presentation of analyzable tasks. On the other hand, rich media is more effective for non-analyzable tasks (Liu et al., 2009). In general, the richness of a communication channel may be influenced by the medium's capacity for immediate feedback, language variety, personalization, and the number of (observable and non-observable) cues and channels used, which include gestures, tone, and body language, among other cues (Daft & Lengel, 1986). Face-to-face interactions are considered to be the richest form of information processing because the medium is capable of providing immediate feedback (Daft & Lengel, 1984). These four elements explain why media richness can lead to different user experiences in blogs (Chang & Yang, 2013), e-learning (Hsieh & Cho, 2011; Liu et al., 2009; Zhao et al., 2020), navigation systems (Lin & Chen, 2015), instant messaging (Wang et al., 2012), and mobile data services (Chen & Demirci, 2019).

In the universe of AI technologies, the degree to which users can have access to all four components varies (Hsieh & Lee, 2021). With respect to personalized video news, users can experience immediate feedback from the system, a rich variety of language, different degrees of personalization, and a variety of channels and cues generated by AI technology. Although the possibility of having auditory and visual information makes human-computer interaction much richer compared to text communications (Hsieh & Lee, 2021), both the quality of information (equivocality) and the delivery methods are still determinants for user satisfaction and technology acceptance (Han & Yang, 2018; Kim et al., 2020).

Together, perceived intelligence, social attraction, and media richness are capable of providing a rich perspective regarding the main factors that influence users' reception of technology. However, it is still necessary to look into the core element of this research: trust.

2.7. Trust

Trust is a construct within studies in distinct disciplines, including psychology, management, technology, social sciences, and other areas of knowledge (Zhang et al., 2019). Hence, notions of trust vary according to the subject and area of study. In psychology, for example, trust is defined as "an expectancy held by an individual or group that the word, promise, or verbal or written statement of another person or group can be relied upon" (Rotter, 1967, p. 651). Alternatively, trust can also be recognized in terms of confidence among parties (Sabel, 1993). In management, definitions can change and be adapted according to the field of study. Trust can be considered "the perceived credibility and benevolence of a target of trust" (Doney & Cannon, 1997, p. 36). In the present research context, trust might be identified as the extent to which news consumers perceive video news as credible, reliable, and trustworthy.

Trust also tends to be a complex concept (Yang et al., 2015). It derives from social interactions and is a key aspect of them (Lu et al., 2016; Thielmann, & Hilbig, 2015). A trustful social relationship is multidimensional, given that it depends on two distinct parties: the trustee and the trustor (Balakrishnan & Dwivedi, 2021b; Chattaraman et al., 2019). While trust is the action of a trustor, trustworthiness is the feature of a person (or an element) that is the object of trust (Corritore et al., 2003). Likewise, trust and trustworthiness are correlated: Trust only exists if the trustor presents trustworthiness (Solomon & Flores, 2001).

In the context of AI technologies, trust can be examined in two different ways: as a human-like construct (non-functional quality) or as a system-like construct (functional quality; Balakrishnan & Dwivedi, 2021b; Shin, 2021a; Wirtz et al., 2018). The former analyzes non-functional evaluations including, for instance, emotions, satisfaction, and normative values. The latter examines functional assessments, including perceived notions of personalization, accuracy, functionality, and usefulness. The present study only considers trust as a system-like construct. Therefore, it only examines the functional aspects of the construct, excluding the evaluation of non-functional elements.

Recent literature considers trust to be a key construct in technology-acceptance studies due to its capability of influencing user behavior, attitude, and, consequently, acceptance (Acharya & Mekker, 2022; Chang & Yang, 2013; Lee & Choi, 2017; Lippert & Davis, 2006; Liu et al., 2022; Zhang, et al., 2019). That is, trust as a system-like construct may be capable of conditioning both user behavior and technology acceptance.

In the universe of news recommendation systems, trust is linked to the accuracy with which recommendations are made (Shin, 2021a; Shin, 2021b). That is, the precision with which news is recommended follows the demands and tastes of users. In a period when trust in news is declining in many Western countries (Hanitzsch et al., 2018), it would be interesting to analyze whether users would demonstrate signs of trust in the technology of personalizing news.

The recent development of AI-generated personalized news still has uncertain effects on audiences. Conceptual models are one of the best alternatives for understanding not only the factors that influence audiences but also their implications for those who use the technology. Among the various frameworks, the theory acceptance model (TAM; Davis et al., 1989) certainly deserves attention due to its efficiency and simplicity.

2.8. Theory acceptance model

Many different theories have been developed to analyze and comprehend human behavior. The theory of reasoned action (TRA; Fishbein & Ajzen, 1975), the TAM (Davis et al., 1989), and the unified theory acceptance and use of technology (UTAUT; Venkatesh et al., 2003) are just a couple of examples of the most famous theories that are still used and discussed by scholars.

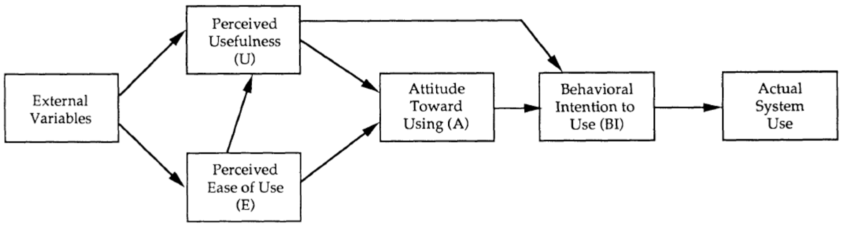
Firstly, the TRA by Ajzen and Fishbein (1975) is a general model based on social psychology and focused on understanding a person's behavior based on his/her attitudes. In summary, the theory proposes that someone's behavior is a result of the combination of his/her subjective norm (beliefs and motivations) and his/her attitude toward the behavior.

Secondly, the TAM is an adaptation of TRA specially created to comprehend user acceptance of information systems (Davis et al., 1989). TAM was developed by Fred Davis in 1986, becoming a fundamental model to comprehend human usage behaviors towards a possible acceptance/rejection of new information technologies (Marangunić & Granić, 2015).

To measure the acceptance/rejection of a new technology, TAM proposes six distinct constructs (also called beliefs or factors) that are divided into different levels. At the first level, Davis et al. (1989) considered external variables as a construct that results from the user's internal characteristics and the system's features. External variables can influence both perceived usefulness (U) and perceived ease of use (E) in different ways. Perceived usefulness is defined as "the degree to which a person believes that using a particular system will enhance his or her job performance" (Davis, 1989, p. 320), and perceived ease of use is "the degree to which a person believes that using a particular system would be free of effort" (Davis, 1989, p. 320). While perceived usefulness corresponds to the user's view on the extent to which a technology is capable of enhancing his/her work, perceived ease of use measures the user's belief about what the use of technology requires in terms of effort. Together, perceived usefulness and perceived ease of use are the main determinants of user acceptance located at the second level of the model.

Figure 2.1

Theory acceptance model



Note: Adapted from "User Acceptance of Computer Technology: A Comparison of Two Theoretical Models" by Davis et al., 1989, *Management Science,* 35, 8, p. 985.

The combination of both perceived usefulness and perceived ease of use composes the user's attitude towards using the system (A), a third-level construct. The fourth and subsequent level of the model is constituted by the behavioral intention to use (BI). This construct is determined by the combination of attitude and perceived usefulness and is the last step in defining the system's actual usage, which is the result of the theory.

The TAM has been the primary model of technology acceptance. It became a framework that is famous for its robustness, parsimony, and power.

However, while TAM's simplicity is its main strength, it can also be its main weakness (Venkatesh, 2000). The theory is essential in identifying perceived ease of use and perceived usefulness as main constructs in technology acceptance, but it does not consider other variables that may also play a determinant role in the acceptance process.

Alternative frameworks were designed with the goal of examining factors that TAM does not take into consideration. The theory acceptance model 2 (TAM 2) incorporates into the framework other constructs, including social influence and cognitive social processes (Davis & Venkatesh, 2000; Venkatesh, 2000). Similarly, the theory acceptance model 3 (TAM 3) redesigns an integrated nomological network model (Venkatesh & Bala, 2008).

As an attempt to unify the various acceptance models, the UTAUT was proposed (Venkatesh et al., 2003). The core idea of the theory is that technology adoption and usage are connected to contextual factors and technology attributes (Aw et al., 2021). Like the extensions of TAM, the unified theory of acceptance and use of technology 2 (UTAUT 2) incorporates three additional constructs, namely hedonic motivation, price value, and habit, and drops voluntariness of use (Venkatesh et al., 2012). In total, the UTAUT 2 considers 10 different constructs and assumes that some of them, including gender, age, and experience, directly influence other first-level constructs.

Lastly, considering the potential future development of AI-generated personalized news videos, the TRA, TAM, UTAUT, and their respective extensions provide useful tools and insights with respect to the study and understanding of human behaviors toward the acceptance of new technology. The abundance of constructs provided by the models is also important in terms of measuring and comprehending how distinct variables impact the user's acceptance of developing technology.

2.9. Conceptual model

When the TAM was introduced (Davis et al., 1989), its main goal was to measure the acceptance/rejection of new technology by its potential users through a simple model with few constructs. Over the years, the TAM has evolved into other theories and has incorporated variables that can play a determinant role in the acceptance of new technologies, as already highlighted. Nevertheless, despite the theoretical evolutions, TAM's simplicity is still relevant to analyzing potential technology acceptance.

In the shifting environment of news media, AI is already a reality capable of shaping the future (Brennen et al., 2022; Linden, 2017; Thorne, 2020). Beyond AI-generated news articles, AI-generated video news has already been identified as an emerging technology (Wang et al., 2022). Hence, the present research intends to verify the trust that users have, compared to human-generated content (traditional video news), in personalized news programs led by AI in OTT video streaming platforms. To this end, the TAM has been slightly adapted and examined to define the seven hypotheses of this study. Figure 2.2 illustrates the conceptual model used.

The conceptual model of this investigation retains TAM's perceived ease of use and perceived usefulness, positioning them at the core of the model. TAM identifies a direct relation between perceived ease of use and perceived usefulness (Davis et al., 1989). Similarly, TAM 2 and TAM 3 also confirm the positive link between both constructs (Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). More modern research has also identified and reproduced this positive relationship when investigating technology acceptance (Acharya & Mekker, 2022; Chang & Yang, 2013; Choung et al., 2022; Lee & Choi, 2017; Lippert & Davis, 2006; Liu et al., 2022; Liu & Tao, 2022; Zhang, et al., 2019). Consequently, the first hypothesis proposes to confirm the relationship between these two constructs in the context of this research.

H1: Perceived ease of use has a positive effect on perceived usefulness in video news.

Positive perceived intelligence on the part of the user may be capable of generating a positive attitude toward the technology (Smith & Sivo, 2012). Additionally, it can enhance the user's experience in such a way that it affects the user's purchase intention (Balakrishnan & Dwivedi, 2021a). The intelligence of an AI technology of personalized news is based on the technological setup, made through machine learning, that identifies and selects content according to the taste of the user. Besides that, the presenter's capacity of expressing anthropomorphic characteristics (e.g., language processing) and human acts can also impact the perceived intelligence by a user (Lee & Chen, 2022; McLean, et al., 2021).

In contrast to perceived usefulness, the perceived intelligence of technology is measured by the competency perceived by the user (Balakrishnan & Dwivedi, 2021a; Bartneck et al., 2009). Therefore, it should be an antecedent of perceived usefulness, considering that AI features are stimuli capable of shaping the user's evaluation of the technology (Lee & Chen, 2022). Hence, a high-quality output should have a positive influence on perceived usefulness (Moussawi et al., 2021).

H2: Perceived intelligence will positively influence perceived usefulness in video news.

Beyond perceived usefulness, social attraction is another component that can have a direct impact on perceived usefulness (Wang et al., 2012; Zhao, et al., 2018). Behind social attraction is a sense of a psychological attraction (or presence) that is conveyed by the (digital) medium (Karahanna & Straub, 1999). It represents the user's involvement in the digital environment (Zhao, et al., 2018). Again, anthropomorphic features and other tools of AI technology provoke stimuli that may affect the user's perception of AI technologies (McLean et al., 2021). Social attraction is a construct of emotional traits nurtured by hedonic, not utilitarian, motives (Hassanein & Head, 2006). Thus, given that social attraction would be another antecedent with a positive influence on perceived usefulness, the third hypothesis has been created as follows:

H3: Social attraction will positively influence perceived usefulness in video news.

Media richness, or the capacity of the medium to deliver rich information, may also play a major role in the perception of a technology (Daft & Lengel, 1986). It not only affects the information exchange among users and the technology, but it may also have a significant impact on both the users' experience (Liu et al., 2009) and their intention to use the technology (Zhao et al., 2020). In an AI-based context, media richness can be enhanced, for example, through language variety, the use of different symbols and signs, personalized responses, and the performance of multiple tasks (Hsieh & Lee, 2021). Consequently, the richness of media can be determinative in influencing users' perceived ease of use (Hsieh & Lee, 2021; Lin & Chen 2015; Wang et al., 2012):

H4: Media richness has a positive impact on perceived ease of use in video news.

Similarly, media richness may also be a determinant in influencing perceived usefulness (Chang & Yang, 2013; Chen & Demirci, 2019; Hsieh & Lee, 2021; Lin & Chen 2015; Liu et al., 2009; Wang et al., 2012). The findings reached by these authors lead to the fifth hypothesis of this study:

H5: Media richness has a positive impact on perceived usefulness in video news.

Finally, one of the main objectives of this research is to analyze the levels of trust that users have in AI-generated personalized news technology. To this end, three constructs compose the core of the conceptual model: perceived ease of use, perceived usefulness, and trust. The relationships between these three constructs were not originally considered in the TAM (Davis et al., 1989), UTAUT (Venkatesh et al., 2003), and their extensions (Davis & Venkatesh, 2000; Venkatesh, 2000; Venkatesh et al., 2012; Venkatesh & Bala, 2008). Nevertheless, other studies have considered the implications of trust and added the construct to their conceptual models (Ghazizadeh et al, 2012; Pavlou, 2003; Xu et al., 2018).

Results highlight that trust can impact system-like constructs in different ways. Trust can be regarded as a variable that can influence both the perceived usefulness and the perceived ease of use (Ghazizadeh et al, 2012; Ha & Stoel, 2009; Liu & Tao, 2022; Ortega & Román González, 2011; Pavlou, 2003; Yang et al., 2015). For example, Huang et al. (2022c) identify trust as a second-order construct with sufficient power to positively influence perceived usefulness. On the other hand, trust can be directly affected by perceived ease of use and perceived usefulness (Dikmen & Burns, 2017; Flavián et al., 2006; Liu & Tao, 2022; Roca et al., 2009; Shin, 2022; Xu et al., 2022 Yang et al., 2015; Zhang, 2010). Both constructs also have the power to influence trust. Therefore, depending on the situation, trust can be identified as an antecedent or a descendant of perceived ease of use and perceived usefulness (Acharya & Mekker, 2022).

Considering these notions, the present study intends to analyze and measure trust as a *result* of user experience. Trust has been positioned as a *descendant* of perceived ease of use and perceived usefulness, that is, a construct which is influenced by perceived ease of use and perceived usefulness. Hypotheses H6 and H7 intend to respectively analyze the relationship between perceived ease of use and trust and between perceived usefulness and trust in the context of video news.

H6: Perceived ease of use positively influences trust in video news.

H7: Perceived usefulness positively influences trust in video news.

Finally, so as to respond to the third objective of this study, it is indispensable to contrast the levels of trust among those who have experienced AI-generated personalized video news and those who have watched human-generated video news.

In the context of AI-journalism, prior research into automated news reveals that AI-generated articles present similar levels of perceived credibility compared to human-generated articles (Clerwall, 2014; Graefe et al., 2017; van der Kaa & Krahmer, 2014).

In analyzing the universe of video news, the technical dimension also must be taken into account because the video is considered to be a richer kind of media compared to text communications (Hsieh & Lee, 2021). Visual appeal has a strong influence on users' perceived ease of use, perceived usefulness, and trust (Pegnate & Sarathy, 2017). Nowadays, technology can resemble human interactions through human-like avatars (Han & Yang, 2018; Hsieh & Lee, 2021) who both look and act like human beings (Kaplan & Haenlein, 2019). Beyond the visual elements, user experience with the system is essential in defining perceived ease of use (Liu et al., 2022) and plays a mediating role in composing the user's perceived usefulness of the system (Venkatesh & Bala, 2008) and thus trust in the system (Shin, 2021b).

Therefore, by understanding that the experience might be similar for those who have watched human-generated content in comparison to those who have experienced AI-generated content, the following moderation hypotheses have been developed:

H6a (moderation): Perceived ease of use has similar effects on trust in human-generated video news and AI-generated personalized video news.

H7a (moderation): Perceived usefulness has similar effects on trust in human-generated video news and AI-generated video news.

Below is the summary of all hypotheses analyzed in this investigation.

Table 2.1

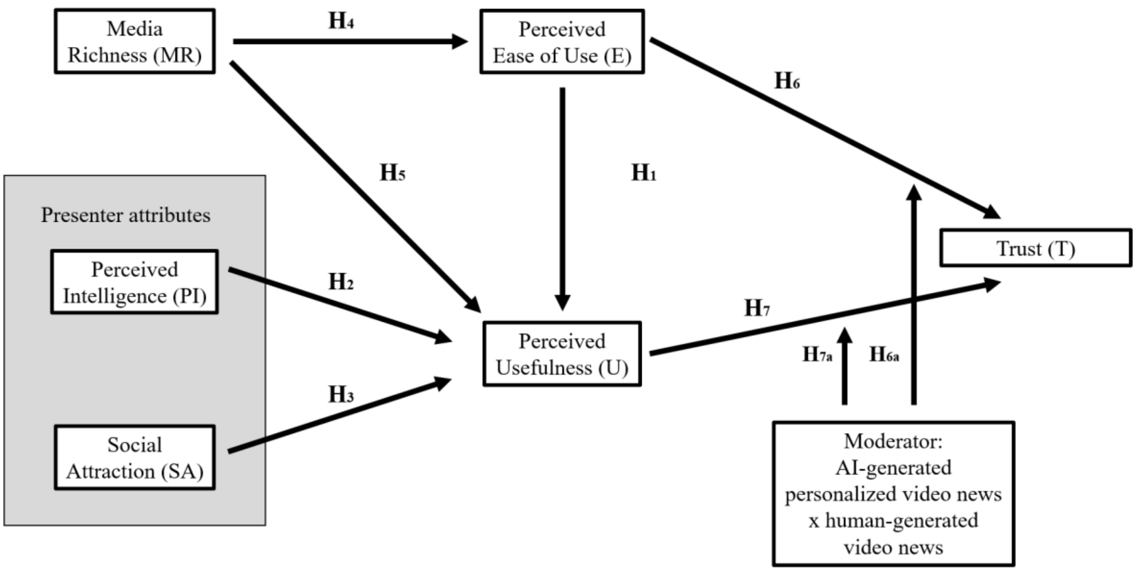
Summary of Hypotheses

H1: Perceived ease of use has a positive effect on perceived usefulness in video news.
H2: Perceived intelligence will positively influence perceived usefulness in video news.
H3: Social attraction will positively influence perceived usefulness in video news.
H4: Media richness has a positive impact on perceived ease of use in video news.
H5: Media richness has a positive impact on perceived usefulness in video news.
H6: Perceived ease of use positively influences trust in video news.
H6a (moderation): Perceived ease of use has similar effects on trust in human-generated video news and in AI-generated personalized video news.
H7: Perceived usefulness positively influences trust in video news.
H7a (moderation): Perceived usefulness has similar effects on trust in human-generated video news and in AI-generated video news.

Together, the six constructs and the seven hypotheses of this investigation perform the following conceptual model:

Figure 2.2

Conceptual model



Note: Conceptual model with hypotheses.

CHAPTER 3

Research methodology

The present study examines the perceptions of trust that users have in AI-generated personalized video news, taking into consideration the conceptual model of this study and its hypotheses. This investigation uses a quantitative research method in which numerical data were gathered to test the hypotheses presented in the previous section.

3.1. The experiment

Primary data were collected using online experiments followed by questionnaires that were introduced and shared using Google Forms, an online form creator developed by Google LLC. The selected sample for the experiment was a convenience sample that did not include any kind of targeted group. Forms were sent through a link that was followed by a brief introduction to the research. No financial benefit nor any kind of monetary gratification was conceded for individuals who decided to participate in this investigation.

In terms of sampling limitations, the experiment was limited to those who are literate, either in English or in Portuguese; have Internet access; can use Google Forms; and consented to participate in the experiment.

3.1.1. Experimental design and measures

The experiment was conducted with two different groups. One of them watched an introductory news video of 46s regarding brain hacking. This video was retrieved from a TV program from the British Broadcasting Corporation, an international news broadcaster, which had a human anchor as its only presenter (British Broadcasting Corporation, 2018).

The other group watched a similar introductory news video of 48s regarding brain hacking that was entirely made with an AI avatar. The AI-generated video was created through Synthesia, an AI video generation platform, reproducing the same speech and scenario of the original video. The only difference in the experiment between the groups, apart from the video production, was that the second group also had a description regarding the technology of personalizing news that could be implemented with AI-generated content.

The experiment was divided into three different sections. Participants who did not complete all questions of the section were not allowed to resume the next part of the experiment. The first section was a brief introduction to the research; a consent note was requested. In the second section, participants encountered the video (either the original/human video or the AI-generated video) and four general questions regarding their personal information (gender, age, marital status, and nationality). The third and final section consisted of a questionnaire comprising 42 closed-ended questions, which was the most appropriate measurement mechanism for the study. For the last section, answers were divided into a 7-point Likert scale of agreement (Strongly Agree, Disagree, Somewhat Agree, Neither Agree nor Disagree, Somewhat Disagree, Disagree, and Strongly Disagree).

The second section of the study tried to segment and obtain further information about the sample. In this section, four questions were asked, including an open question where respondents had to type their answer (nationality). A summary of the second section of the experiment can be found as follows:

Table 3.1

Survey questions

Questions	Type	Possible Answers
Gender	Closed	Male; Female; non-binary; Prefer not to say; Other:
Age	Closed	10-19; 20-29; 30-39; 40-49; 50-59; 60-69; 70 +;
Marital Status	Closed	Single; Married; Divorced; Widowed; Other;
Nationality	Open	Open.

Note: Summary of the answers of the second section of the experiment.

For the third and final section, 42 questions were asked. All of them were selected and adapted from previous studies that examined the same constructs. Reputable authors were taken into consideration as well as their original studies. A marker variable (MV) was also included to assess the common method variance in the experience. The common method variance items were randomly distributed throughout the experiment.

Questions were adapted according to the context of the study but always tried to maintain the originality of the referred source. The adaptations are demonstrated in greater detail below:

Table 3.2

Questions and loading

Construct	Adapted Item (original vídeo)	Adapted Item (AI-generated video)	Source	Loading
Presenter attributes (perceived intelligence; PI)	The presenter:			
	appears competent		Bartneck et al., 2009, p. 79	PI1
	is knowledgeable			PI2
	is responsible			PI3
	is intelligent			PI4
	is sensible			PI5
Presenter attributes (social attraction; SA)	The presenter could be a friend of mine		McCroskey & McCain, 1974, p. 264	SA1
	I would like to have a friendly chat with the presenter			SA2
	It would be difficult to meet and talk with the presenter			SA3
	We could never establish a personal friendship with each other			SA4
	The presenter just wouldn't fit into my circle of friends			SA5
	The presenter would be pleasant to be with			SA6
	I feel I know the presenter personally			SA7
	The presenter is personally offensive to me			SA8
	I don't care if I ever get to meet the presenter			SA9
	I sometimes wish I were more like the presenter			SA10
Media richness (MR)	The presenter has the ability to:			
	give and receive timely feedback		Lee et al., 2007, p. 2072	MR1
	design messages to my own or other's requirements			MR2
	transmit a variety of different cues (through sounds, images and gestures)			MR3
	use rich and varied language			MR4
	design messages to your own or others' personal situation			MR5
	convey multiple types of information			MR6
	transmit varied symbols			MR7
	provide immediate feedback			MR8
Perceived ease of use (E)	Learning to operate this type of media would be easy for me	Learning to operate the Personalized News Technology would be easy for me	Davis et al., 1989, p. 340	E1
	I would find it easy to get this type of media to do what I want it to do	I would find it easy to get the Personalized News Technology to do what I want it to do		E2
	It would be easy for me to become skillful at using this type of media	It would be easy for me to become skillful at using the Personalized News Technology		E3

	I would find this type of media easy to use	I would find the Personalized News Technology easy to use		E4
	My interaction with this type of media would be clear and understandable	My interaction with the Personalized News Technology would be clear and understandable	Davis et al., 1989, p. 991	E5
	I would find this type of media to be flexible to interact with	I would find the Personalized News Technology to be flexible to interact with		E6
Perceived usefulness (U)	This type of media:	The Personalized News Technology:	Hsieh & Lee, 2021, p. 281	
	provides good quality of information			U1
	increases my effectiveness for informed choices			U2
	is useful for assessing information			U3
	improves my performance in assessing information			U4
	increases the quality or output of my life/work		Chan-Olmsted et al., 2013, p. 134-135	U5
	enhances the productivity of my life/work			U6
	helps my life/work			U7
Trust (T)	Even if not monitored, I'd trust this type of media to do the right job	Even if not monitored, I'd trust the Personalized News Technology to do the right job	Gefen, 2000, p. 735	T1
	I trust this type of media	I trust the Personalized News Technology		T2
	I believe this type of media is trustworthy	I believe the Personalized News Technology is trustworthy		T3
Common method variance (CMV)	I prefer blue to other colors		Simmering et al., 2015, p. 491	MV1
	I like the color blue			MV2
	I like blue clothes			MV3

Note: Adapted questions from the literature and their corresponding loading.

Some of these questions were initially used on a 5-point Likert scale, namely those from Bartneck et al. (2009). For consistency, those questions were converted into the 7-Likert scale to be similar to the others used in the study. Numerically, answers were translated into the extension of agreement to each of the 42 statements listed above (1 = Strongly Disagree; 2 = Disagree; 3 = Somewhat Disagree; 4 = Neither Agree nor Disagree; 5 = Somewhat Agree; 6 = Agree; 7 = Strongly Agree).

Out of the 42 statements, SA3, SA4, SA5, SA8, and SA9 of social attraction had inverted scales. Statements were kept as in the original source (McCroskey & McCain, 1974), and their results were adapted to the same scale of the experiment.

3.1.2. Pre-experiment

Before running the final experiment of this research, a small pre-experiment was tested to check for possible flaws and necessary adjustments. Biggam (2008, p. 102) recommends a pilot study for preparing the data collection.

For the pre-experiment, an AI-generated video of 11s was created to reproduce, on a smaller scale, what the experiment would be like. The video was followed by the questionnaire, which was divided into general and closed-ended questions scaling from one to seven. In total, the pre-experiment had 18 participants. Responses were used to calculate the internal consistency of the study, through Cronbach's alpha, for the six constructs of this research. Results were the following: perceived intelligence (α = 0.831), social attraction (α = 0.737), media richness (α = 0.837), perceived ease of use (α = 0.747), perceived usefulness (α = 0.952), and trust (α = 0.855). Despite the small population, results were within the minimal requirement of the scale ($\alpha > 0.7$) for all six variables; therefore, the author decided to proceed with the initial scales.

The pre-experiment was also a great opportunity to receive qualitative feedback from respondents, who actively commented on their participation in the experiment. Some respondents demonstrated that were not sufficiently familiar with the language of the experiment, which was English. From both the received feedback and the fact that the research would be carried out with a convenience sample, a Portuguese version of the questionnaire was also developed for respondents who were not comfortable with the English questionnaire.

3.1.3. Data collection

Assuming that almost every individual would be able to use and benefit from the personalized news technology, no age, geographic, or gender restrictions were considered in this survey.

The convenience sampling technique, which is a non-random method, was performed in this study. Individuals with convenient access were contacted by the author through online channels that included WhatsApp, LinkedIn, Instagram, e-mail, Microsoft Teams, and Facebook between April and May 2022. Respondents were randomly divided by the author into the two proposed groups of this research. Participants were not aware of the existence of two different surveys, nor did they have the chance to choose the one they would rather participate in.

Besides the researcher's personal and professional networks, online groups of researchers that propose an exchange of surveys were also used to collect data.

In total, 306 respondents participated in the experiment, including 152 answers for Experiment 1 and 154 answers for Experiment 2, as presented in Table 3.3.

Table 3.3

Number of respondents by group

N = 306	Frequency
AI Presenter (Experiment 1)	152
Human Presenter (Experiment 2)	154

CHAPTER 4

Data analysis

The present chapter describes and examines data that were collected for this research. Starting from a broader analysis, this section aims to first understand the nature of the collected data. After the demographic description, the collected data are explored considering the conceptual model of this study and the relationship of its constructs in the inner and outer models as well as the multigroup analysis.

4.1. Demographic description

The sample of this investigation (Table 4.1) comprises 306 respondents of different genders, multiple ages, marital statuses, and nationalities.

Concerning the genders of the selected sample, more than 67.3% of the respondents belong to the female gender. For age, the most represented age group is between 20 and 29 years old, with 63% of the total sample population. This result was expected, considering that the experiment was carried out digitally and shared through social media. The second-largest group is between 40 and 49 years old, followed by those between 30 and 39 years of age. Statistically, the average age of the sample is 43, and the mean is 28 years old.

In terms of marital status, it is possible to notice in the sample a significant majority of single respondents, who represent almost 73% of the total population, or 222 people. Finally, regarding the geographic origin of the sample, this investigation managed to get representatives from six different continents, including North and South America, Europe, Africa, Asia, and Oceania. Brazilian and Portuguese respondents are the most represented nationalities, with 27.5% and 19% of the population respectively, mainly due to the convenience sample technique used in the experiment. However, even excluding the top six nationalities (Brazilian, Portuguese, Chinese, German, British, and Dutch), other national groups together represent 38.9% of the sample. This figure highlights the geographical diversity of the population that is represented in the sample.

Table 4.1

Demographic Report

N = 306	Frequency	%
Gender		
Female	206	67.3%
Male	99	32.4%
Prefer not to Say	1	0.3%
Age		

10-19	18	5.9%
20-29	193	63.1%
30-39	28	9.2%
40-49	34	11.1%
50-59	22	7.2%
60-69	8	2.6%
70+	3	1.0%
Marital Status		
Divorced	10	3.3%
Married	54	17.6%
Other	17	5.6%
Single	222	72.5%
Widowed	3	1.0%
Nationality		
Brazil	84	27.5%
China	9	2.9%
Germany	15	4.9%
Great Britain	8	2.6%
Other	119	38.9%
Portugal	58	19.0%
The Netherlands	13	4.2%
Total	306	

Note: Demographic report divided by gender, age, marital status, and nationality.

4.2. Common method variance

Before moving on to the partial least squares structural equation modeling (PLS-SEM) analysis, it is essential to assess potential variances that may result from the data collection method used in the research. The common method variance (CMV) is defined as "variance that is attributable to the measurement method rather than to the constructs the measures represent" (Podsakoff et al., 2003, p. 879). In other words, the method variance happens when responses not only express the construct but also the measurement method in which they were established (Baumgartner & Weijters, 2021). The presence of CMV might create a false consistency, which is a supposed correlation between constructs that is a result of a mutual source (Podsakoff et al., 2003).

Even though CMV is a commonly shared concern among scholars, there are different research methods to assess and deal with CMV. This study investigates the presence of common method bias through the calculation of the full-collinearity method (Kock, 2014; Kock & Lynn, 2012) using the marker variable proposed by Simmering et al. (2015).

The first CMV assessment calculates the variance inflation factor (VIF) in the conceptual model without any marker variable. Values below 3.3 do not present collinearity issues and therefore are free from common method biases (Kock, 2014; Kock & Lynn, 2012). Results (Annex A section) vary between 1.000 and 1.418, respecting the 3.3 threshold indicated by Kock and Lynn (2012). No common method bias has been identified in this first assessment.

The second assessment uses the vertical (or classic) collinearity including the adaptation of the marker variable proposed by Simmering et al. (2015). Once more, no common method bias has been identified, given that the VIF values for the inner model (included in the Annex A section) do not exceed the 3.3 mark (Kock, 2014; Kock & Lynn, 2012). The highest result obtained is 1.987, far below the common method bias threshold.

Therefore, results from both CMV assessments conclude that the conceptual model of this study is free of common method variance.

4.3. PLS-SEM results

This study analyzes and interprets data using the PLS-SEM, which is used not only in management but in various distinct disciplines, including strategic management, e-business, marketing, consumer behavior, and management information systems (Henseler et al., 2009). The PLS-SEM allows researchers to evaluate and assess complex relationships between dependent and independent variables (Hair et al., 2013). Thus, it is considered to be a suitable method for this kind of study.

An advantage of the PLS-SEM model is the possibility of working with smaller sample sizes in comparison to the covariance-based structural equation modeling (CB-SEM). According to Hair et al. (2021), the model requires a sample size of 10 times the maximum number of arrows that point at a latent variable. Considering that perceived usefulness is the latent variable, with more connections with independent variables, 4 in total, the model would require a minimum N of 40 responses. That number was easily overtaken by the 306 respondents in this research. Cohen's (1992) approach adds that a significant sample size with a 5% probability error and a minimum R^2 of 0.25 for the latent variable with more arrows needs to have a minimum N of 65 observations. Again, the number of respondents complies with the rule.

Once the expected sample size has been met, it is possible to move forward to the analysis of the PLS-SEM conceptual model, which is divided into two. First, the outer model (measurement model) indicates the relationships between the constructs and the indicator variables. Second, the inner model (structural model) investigates the direct connections between constructs (Hair et al., 2021). The following sections take a deeper look into PLS-SEM outer and inner models through the PLS algorithm and bootstrapping calculation techniques.

4.3.1. Outer model

The outer model of this investigation analyzes four main aspects of the conceptual model: internal consistency reliability, convergent validity, discriminant validity, and multicollinearity. The results are summarized in Table 4.2.

The first step in the outer model is to assess the indicator reliability, that is, to verify how much of the indicator variance is explained by the construct (Hair et al., 2021). Although all indicators have already been tested and used in previous studies, some of them may not be adequate for this particular study.

Indicator loadings that are above 0.7 (>0.7) are recommended because they are an adequate indicator of reliability, and indicators with an outer loading below 0.4 should be eliminated. Indicator loadings that are between 0.4 and 0.7 indicate lower reliability and might be considered for removal, depending on both their content validity and their impact on the internal consistency reliability of the research. If the removal of the indicator increases the construct's composite reliability (CR) or average variance extracted (AVE), the indicator should be removed (Hair et al., 2021).

From the interpretation of the initial results, indicators of social attraction (SA3, SA4, SA8, and SA9) are deleted due to their loadings below 0.4. Similarly, other indicators with loadings between 0.4 and 0.7 are also removed after generating a positive effect either in CR or AVE. These indicators belonged to perceived intelligence (PI5), media richness (MR8, MR1, and MR2), and again social attraction (SA5, SA7, and SA10). Despite the considerable number of removals in social attraction (seven in total), it is crucial to highlight that the construct still complies with the instruction of having at least three indicators per construct so as to avoid unstable solutions (Anderson & Gerbing, 1988; Bagozzi & Yi, 2012; Baumgartner & Homburg, 1996).

Convergent validity is also analyzed through the calculation of the AVE. Results show that all constructs present AVE values above the minimum of 0.5 (Hair et al., 2021). Therefore, results indicate sufficient levels of reliability in this conceptual model.

Similarly, internal consistency reliability results are satisfactory for all constructs in this study. Values for Cronbach's alpha (α) and the CR are all above the required minimum of 0.6 and the recommended value of 0.7 (Henseler et al., 2009).

Table 4.2

Final results - constructs, indicators, and reliability indicators

Construct	Adapted Item (original video)	Adapted Item (AI-generated video)	Source	Outer Loading
Presenter attributes (perceived intelligence; PI) α: 0.799	The presenter:		Bartneck et al., 2009, p. 79	
	appears competent			PI1 (0.727)
	is knowledgeable			PI2 (0.865)

CR: 0.818 AVE: 0.623	is responsible			PI3 (0.752)
	is intelligent			PI4 (0.806)
Presenter attributes (social attraction; SA)	The presenter could be a friend of mine		McCroskey & McCain, 1974, p. 264	SA1 (0.766)
	I would like to have a friendly chat with the presenter			SA2 (0.907)
α: 0.763 CR: 0.844 AVE: 0.674	The presenter would be pleasant to be with			SA6 (0.783)
Media richness (MR)	The presenter has the ability to:		Lee et al., 2007, p. 2072	
	transmit a variety of different cues beyond the pure text messages			MR3 (0.791)
α: 0.836 CR: 0.840	use rich and varied language			MR4 (0.747)
AVE: 0.604	design messages to your own or others' personal situation			MR5 (0.748)
	convey multiple types of information			MR6 (0.826)
	transmit varied symbols			MR7 (0.771)
Perceived ease of use (E)	Learning to operate this type of media would be easy for me	Learning to operate the Personalized News Technology would be easy for me	Davis et al., 1989, p. 340	E1 (0.743)
α: 0.874 CR: 0.894 AVE: 0.609	I would find it easy to get this type of media to do what I want it to do	I would find it easy to get the Personalized News Technology to do what I want it to do		E2 (0.795)
	It would be easy for me to become skillful at using this type of media	It would be easy for me to become skillful at using the Personalized News Technology		E3 (0.759)
	I would find this type of media easy to use	I would find the Personalized News Technology easy to use		E4 (0.789)
	My interaction with this type of media would be clear and understandable	My interaction with the Personalized News Technology would be clear and understandable	Davis et al., 1989, p. 991	E5 (0.846)
	I would find this type of media to be flexible to interact with	I would find the Personalized News Technology to be flexible to interact with		E6 (0.748)
Perceived usefulness (U)	This type of media:	The Personalized News Technology:	Hsieh & Lee, 2021, p. 281	
	provides good quality of information			U1 (0.753)

	increases my effectiveness for informed choices			U2 (0.837)
α: 0.896 CR: 0.899 AVE: 0.616	is useful for assessing information			U3 (0.787)
	improves my performance in assessing information			U4 (0.826)
	increases the quality or output of my life/work		Chan-Olmsted et al., 2013, p. 134-135	U5 (0.785)
	enhances the productivity of my life/work			U6 (0.745)
	helps my life/work			U7 (0.755)
Trust (T) α: 0.859 CR: 0.868 AVE: 0.782	Even if not monitored, I'd trust this type of media to do the right job	Even if not monitored, I'd trust the presenter to do the right job	Gefen, 2000, p. 735	T1 (0.766)
	I trust this type of media	I trust the presenter		T2 (0.907)
	I believe this type of media is trustworthy	I believe the presenter is trustworthy		T3 (0.783)

Note: Selected questions from the literature and their corresponding constructs, indicators, and reliability indicators.

The third step of the outer model is to verify the discriminant validity. Three measurements are used: the cross loadings, the Fornell-Larcker criterion, and finally the heterotrait-monotrait (HTMT).

Starting with the cross loadings, indicators should present higher loadings on their corresponding construct in comparison to the other constructs (Chin, 1998). That is, E2 should have higher loadings on perceived ease of use as opposed to perceived intelligence, for example. According to the results obtained (in the Annex A section), all indicators present higher correlations with their respective constructs, as expected.

The second method for assessing the discriminant validity is the Fornell-Larcker criterion. According to this approach, the squared root of each construct's AVE should be greater than the correlations with other constructs (Fornell & Larcker, 1981). As per the results in Table 4.3, all constructs meet both requirements, indicating suitable discriminant validity.

Table 4.3

Fornell-Larcker criterion and HTMT ratios

	E	MR	PI	U	SA	T
E	0.781					
MR	0.232 (0.250)	0.777				
PI	0.212 (0.235)	0.415 (0.504)	0.789			
U	0.440 (0.465)	0.322 (0.369)	0.403 (0.460)	0.785		
SA	0.107 (0.122)	0.308 (0.382)	0.445 (0.571)	0.274 (0.316)	0.821	
T	0.310 (0.344)	0.182 (0.210)	0.378 (0.441)	0.661 (0.750)	0.309 (0.371)	0.884

Note: Discriminant validity assessment: Fornell-Larcker criterion and HTMT results (in parenthesis).

The third and last method for assessing the discriminant validity is the HTMT proposed by Henseler, Rigle, and Sarstedt (2015). This method is a consistent alternative to cross loadings and the Fornell-Larcker criterion methods, which may not always be effective (Henseler et al., 2014). The rule for the HTMT ratio is to have a value below the threshold of 0.9 for discriminant validity (Hair et al., 2021). As shown in Table 4.3, all constructs present a value below the HTMT ratio threshold, reconfirming the discriminant validity results.

Lastly, it is also necessary to check the collinearity of formative indicators in the model, given that higher correlations tend to increase standard errors. For that measurement, the VIF is used to assess the multicollinearity of indicators. The VIF of this model ranges from 3.114 (T2) to 1.465 (SA6; results in the Annex A section). The rule of thumb is that VIF values should not be greater than 10 (Henseler et al., 2009), while more conservative approaches suggest results below 5 or 3.3 (Kock & Lynn, 2012). Even considering the most conservative values, it is possible to affirm that the results do not reflect multicollinearity issues.

4.3.2. Inner model

If the outer model investigates the relationship between latent variables and their respective indicators, the inner model analyzes the links between latent variables. The inner model of this investigation analyzes the following main aspects of the conceptual model: the model fitness, its multicollinearity and predictive capability, and the effect sizes of each construct.

Starting with the model fitness, the index of the standardized root mean square residual (SRMR) defines a good fit as a model that presents results between 0 and 0.08 (Hu & Bentler, 1999). The SRMR of the model is 0.071, which indicates a well-fit model (full summary available in the Annex A section).

As in the outer model, it is possible to review the VIF for the inner model, now considering the multicollinearity of latent variables. Results were already discussed in the Common method variance section, highlighting that no collinearity issues have been identified.

The model fitness and potential collinearity issues having been verified, it is time to look at the predictive capabilities of the model. This assessment is divided into three parts: first, the coefficient of determination (the R-squared); second, the cross-validated redundancy; and third, the path coefficients.

The R-squared (R^2) indicates the extent to which the variance of one construct influences the variance of another independent construct. R-squared values are expected to be within the range of 0 to 1. The results of 0.19, 0.33, and 0.67 respectively correspond to weak, moderate, and strong correlations (Chin, 1999). The results show a moderate value for trust (0.438) and weak values for perceived usefulness (0.314) and perceived ease of use (0.054).

The Stone-Geisser's Q^2 value verifies the model's predictive relevance (Geisser, 1974; Stone, 1974). The coefficient indicates the model's capacity to predict the indicators of the endogenous constructs (Henseler et al., 2009). If the Q^2 value is greater than 0, the model's predictive accuracy is confirmed for the verified endogenous construct. The Q^2 values can be obtained through the blindfolding calculation, with an omission distance between 5 and 10 (Hair et al., 2017). An omission distance of 7 was chosen in the calculations. The results are the following: perceived ease of use (0.041), perceived usefulness (0.172), and trust (0.117). Given that all of them are above 0, it is possible to conclude that the model has predictive relevance.

Table 4.4

R-squared results

	R Square	R Square Adjusted	Q^2
Perceived ease of use	0.054	0.051	0.041
Perceived usefulness	0.314	0.305	0.172
Trust	0.438	0.434	0.117

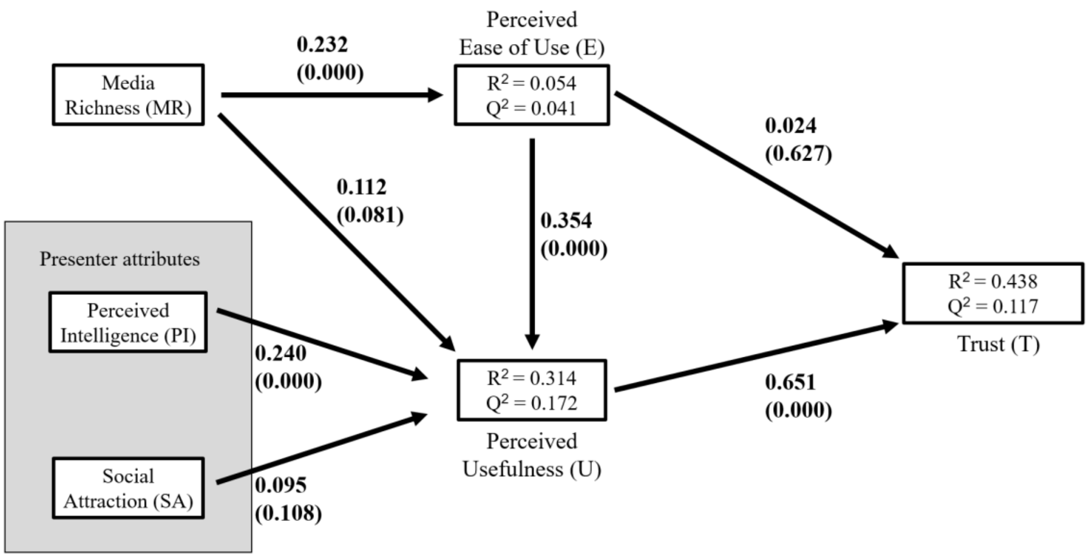
Note: R-squared results for perceived ease of use, perceived usefulness and trust.

When considering the interaction between any two constructs in the inner model, it is necessary to examine three core elements: the constructs' path coefficients (β), their t-values, and their p-values. Starting with the significance levels expressed through the p-values and t-values, at least three relationships do not demonstrate statistical significance. Perceived ease of use → trust ($\beta = 0.024$; $t = 0.486$; $p = 0.627$), media richness → perceived usefulness ($\beta = 0.112$; $t = 1.744$; $p = 0.081$), and social attraction → perceived usefulness ($\beta = 0.095$; $t = 1.607$; $p = 0.108$) present p-values below 0.05 and t-values below 1.96 (Hair et al., 2021). Hence, for a confidence interval of 95%, these three relationships are not statistically significant.

The remaining four relationships are statistically significant. By looking at their path coefficients, it is possible to identify two relationships with considerable low impact among constructs: media richness → perceived ease of use (β = 0.232; t = 4.406; p = 0.000) and perceived intelligence → perceived usefulness (β = 0.240; t = 3.985; p = 0.000). That is, in terms of perceived intelligence → perceived usefulness (β = 0.240; t = 3.985; p = 0.00), by increasing the PI by 1 standard deviation unit, U will increase by 0.240 standard deviation units. Similarly, there is one relationship with medium effect among its variables, namely perceived ease of use → perceived usefulness (β = 0.354; t = 6.207; p = 0.000), and one relationship with a high degree of influence, namely perceived usefulness → trust (β = 0.651; t = 15.618; p = 0.000).

Figure 4.1

Conceptual model with results



Note: Conceptual model with hypotheses' significance: R^2, Q^2 values, path coefficients, and p-values (in parenthesis).

Table 4.5

Total effects

	Original sample (O)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	f-square (f^2)
E -> U	0.354	0.057	6.207	0.000	0.169
E -> T	0.024	0.049	0.486	0.627	0.001
MR -> E	0.232	0.053	4.406	0.000	0.057
MR -> U	0.112	0.064	1.744	0.081	0.014
PI -> U	0.240	0.060	3.985	0.000	0.059
U -> T	0.651	0.042	15.618	0.000	0.607
SA -> U	0.095	0.059	1.607	0.108	0.010

Note: Hypotheses and their corresponding path coefficients, standard deviation, t-values, p-values, and f-squared results.

Another complementary assessment for the analysis is the calculation of the effect size of each construct through f^2 (f-squared). The results show different degrees of effect. A small effect size has an f^2 value between 0.02 and 0.15, a medium effect size is located between 0.15 and 0.35, and a large effect size is beyond the 0.35 mark (Cohen, 1988, p. 414). Once more, both media richness → perceived usefulness (0.014) and social attraction → perceived usefulness (0.010) present small size effects. The relationship of perceived ease of use → trust (0.001) presents no effect, considering that the result is below the 0.2 cut-off. Media richness → perceived ease of use (0.057) and perceived intelligence → perceived usefulness (0.059) present medium effect sizes, while perceived ease → perceived usefulness (0.169) and perceived usefulness → trust (0.607) show large effect sizes.

4.4. Multigroup analysis

The final step in the Data analysis section aims to compare the results of the two different groups studied in this research. Hypotheses H6a and H7a take into account potential variations in trust between users who have experienced AI-generated personalized video news and those who have watched human-generated video news.

In the multigroup analysis, the studied population is divided into two distinct subpopulations, and their parameters are contrasted (Henseler et al., 2009). According to the research, out of 306 respondents, 152 experienced news content entirely generated by an AI presenter (Group 1), with an explanation regarding the personalized news technology; the other 154 respondents watched a video presented by a human presenter (Group 2). The results from these two groups are analyzed and then contrasted.

Through the examination of the construct reliability and validity, the results support the internal consistency for all constructs in both groups through CR values above 0.6 and 0.7 (Henseler et al., 2009). In addition, the latent variables of both groups present a significant level of reliability, with Cronbach's alpha above 0.7. The only exception happens with social attraction, below the 0.7 mark only for those who watched the human presenter (Group 2). Finally, the AVE for Groups 1 and 2 is all above 0.5, satisfying the recommended minimum (Hair et al., 2021).

Table 4.6

Reliability and Validity results from Group 1 – AI-generated presenter with personalized news technology

	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Perceived ease of use	0.886	0.918	0.631
Media richness	0.835	0.852	0.602
Perceived intelligence	0.844	0.865	0.681
Perceived usefulness	0.913	0.917	0.657
Social attraction	0.809	0.893	0.722
Trust	0.866	0.885	0.790

Table 4.7

Reliability and Validity results from Group 2 – Human presenter with no personalized news technology

	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Perceived ease of use	0.864	0.868	0.594
Media richness	0.821	0.827	0.581
Perceived intelligence	0.727	0.738	0.547
Perceived usefulness	0.873	0.879	0.566
Social attraction	0.680	0.743	0.597
Trust	0.850	0.852	0.771

Lastly, by comparing the p-values of the MGA analysis, it is possible to argue that there is no statistically significant difference between the two groups for all analyzed relationships. All p-values are greater than 0.05, evidencing the lack of statistical difference among Groups 1 and 2. In conclusion, there is no significant distinction in results between those who have watched the news with a human presenter in comparison to those who have experienced personalized video news technology with an AI-generated presenter.

Table 4.8

MGA results

	β Group 1 – AI	β Group 2 – Human	Permutation p-value
Perceived ease of use -> perceived usefulness	0.414	0.302	0.331
Perceived ease of use -> trust	0.014	0.045	0.745
Media richness -> perceived ease of use	0.281	0.240	0.712
Media richness -> perceived usefulness	0.085	0.121	0.789
Perceived intelligence -> perceived usefulness	0.246	0.235	0.941
Perceived usefulness -> trust	0.708	0.581	0.142
Social attraction -> perceived usefulness	0.050	0.162	0.366

Note: MGA results for Group 1, and Group 2: path coefficients and p-values.

CHAPTER 5

Discussion

As previously stated, this study intended to examine the perception of trust that users might have in AI-generated video news programs that use personalized news technology. For this purpose, a conceptual model was designed, taking into consideration previous literature on the topic. Six constructs were measured and analyzed in seven different relationships and translated into seven hypotheses. Finally, the main goal of the research was to assess the levels of trust in AI-generated personalized video news compared to human-generated video news.

All constructs present positive and satisfactory results of reliability and validity. Similarly, all discriminants show validity and collinearity in the outer-model analysis. According to the results of the inner model, the conceptual model also has good fitness and no collinearity issues. Therefore, the first conclusion that can be drawn is that the model is significant, has valid results, and has good fitness.

For a deeper look into the outer and inner models, it is crucial to examine each one of the seven relationships between constructs.

5.1. Perceived ease of use and perceived usefulness

As implied by the TAM and its extensions, perceived ease of use has a positive effect on perceived usefulness (Davis et al., 1989; Venkatesh & Bala, 2008; Venkatesh & Davis, 2000). Hypothesis 1 is based both on this conclusion and on recent technology-based research that has examined this correlation in blogs (Chang & Yang, 2013), automated vehicles (Acharya & Mekker, 2022; Zhang, et al., 2019), AI voice assistants (Choung et al., 2022), and smart healthcare systems (Liu & Tao, 2022). The results obtained for perceived ease of use → perceived usefulness ($\beta = 0.354$; $t = 6.207$; $p = 0.000$) confirm that the suggestions from the literature are also applicable to this experiment with video news. Hypothesis 1 is therefore accepted.

The user's perceived notions of ease of use impact his/her perceptions of the usefulness of the video news. Likewise, an AI-generated personalized news technology that is easy to use tends to increase the user's impressions of the utility of that technology.

5.2. Perceived intelligence and perceived usefulness

Perceived usefulness can also be influenced by the user's perceived intelligence of the technology. Hypothesis 2 measures this effect between perceived intelligence and perceived usefulness in the context of video news. The construct of perceived intelligence can generate a positive attitude toward the technology (Smith & Sivo, 2012), influence the user's perceived competency (Balakrishnan & Dwivedi, 2021a) and evaluation of the technology (Lee & Chen, 2022), and generate a positive impact on perceived usefulness (Moussawi et al., 2021). The relationship perceived intelligence → perceived usefulness (β = 0.240; t = 3.985; p = 0.000) that was observed in this investigation has similar outcomes to what is suggested in Hypothesis 2. Hence, H2 is also accepted.

The way that users perceive technology capacity tends to influence their perceptions of technology usefulness. In video news, impressions of a competent and intelligent presenter, for example, are linked to the final impression of utility that the news may have on those who watch it. Overall, video news demonstrates the capacity of delivering outputs that are sufficient to affect the perceived usefulness of users.

5.3. Social attraction and perceived usefulness

Alongside perceived intelligence, the presenter's attributes constituted social attraction. The construct attempts to measure the connection that users have with the environment. The link between social attraction and perceived usefulness has been analyzed in experiments, including studies of instant messaging (Wang et al., 2012) and online user reviews (Zhao, et al., 2018). Based on these findings, Hypothesis 3 aims to verify the influence between social attraction and the perceived usefulness of video news.

According to the results of this study, the relationship between social attraction → perceived usefulness (β = 0.095; t = 1.607; p = 0.108) is not statistically significant, which does not support H3. This outcome implies that users might not be sufficiently involved with the digital medium to perceive utility in video news.

A possible explanation for this outcome is linked to the type of content presented in the experiment. Users who are more emotionally involved in the media content present higher levels of social attraction (Xiang et al., 2016). Social attraction levels are directly related to the user’s perceived entertainment value (Lin & Utz, 2017), which could be translated into perceived usefulness. Hence, users' interest in the subject, content, or even news programs generally can influence their perceptions of perceived usefulness (Chan-Olmsted et al., 2013), and social attraction.

The experiment conducted in this investigation contained a large amount of information and a single news video on brain hacking, which is a very particular topic. Therefore, the type of content available in the experiment may have been decisive in the correlation between social attraction and the perceived usefulness of video news.

5.4. Media richness and perceived ease of use

Hypothesis 4 analyzes the correlation between media richness and perceived ease of use in video news. According to recent literature, perceived ease of use should be impacted by media richness (Chang & Yang, 2013; Chen & Demirci, 2019; Hsieh & Lee, 2021; Lin & Chen 2015; Liu et al., 2009; Wang et al., 2012). In addition, media richness may also be a determinant element in influencing the user's intention to use the technology (Zhao et al., 2020).

Media richness → perceived ease of use ($\beta = 0.232$; $t = 4.406$; $p = 0.000$) presents enough results to confirm the existing relationship between both constructs in the context of video news. The results support that, based on media richness theory (Daft & Lengel, 1986), low levels of uncertainty and equivocality tend to effectively increase user interactions with the system (Chang & Yang, 2013), and user satisfaction (Han & Yang, 2018; Kim et al., 2020). The rich transmission of information proves to impact the user experience (Liu et al., 2009). Hence, the user's understanding of effective interaction with the system proves to have a positive influence on perceptions of ease of use. Accordingly, H4 is supported.

5.5. Media richness and perceived usefulness

The fifth hypothesis of this investigation considers the relationship between media richness and perceived usefulness in the context of video news. The literature suggests that media richness plays a key role in the perception that users have of a technology (Daft & Lengel, 1986), in user experience (Liu et al., 2009), and in the user's intention to use the technology (Zhao et al., 2020). H5 is therefore based on sources that reproduced the relationship between media richness and perceived usefulness in different contexts, including instant messaging (Wang et al., 2012), mobile phone navigation systems (Lin & Chen 2015), and AI smart speakers (Hsieh & Lee, 2021).

Contradicting the literature, the results for media richness → perceived usefulness ($\beta = 0.112$; $t = 1.744$; $p = 0.081$) do not confirm the correlation between media richness and perceived usefulness in the video news environment. H5 was therefore rejected.

To understand this result, it is necessary to recall the four factors that influence media richness according to the media richness theory (Daft & Lengel, 1984; 1986), which include the capacity to convey multiple cues, use varied language, provide timely feedback, and personalize. Perceptions of media richness rely directly on the feedback and information exchange between sides (Walter et al., 2015). Although multimedia is considered to be a rich type of media (Cho et al., 2009), the lack of information exchange in news may significantly influence the relationship between media richness and perceived usefulness. Although audiences are not passive at all (Aguirre et al., 2016; Hermida et al., 2012; Hu et al., 2017), news consumption tends to be a one-sided process that lacks an exchange of information between news presenters and their audience.

The lack of communication/interaction between the sides, added to the information overload present in the experiment, might have been a determinant in this result. Large amounts of information can trigger negative impacts on the perceived utility that users have of technology (Hew et al., 2018; Lee et al., 2016; Zhang et al., 2016).

Thus, the information overload combined with the lack of interactivity with the system in the experiment could have affected the relationship between media richness and perceived usefulness.

5.6. Perceived ease of use and trust

The impact of perceived ease of use on trust proved to be non-significant in this research. The results obtained in this investigation for perceived ease of use → trust ($\beta = 0.024$; $t = 0.486$; $p = 0.627$) contradict the literature that measured the same relationship on websites, (Flavián et al., 2006), in online trading services (Roca et al., 2009), SMS advertising (Zhang, 2010), AI smart healthcare services (Liu & Tao, 2022), automated vehicles (Acharya & Mekker, 2022; Zhang et al., 2019), AI voice assistants (Choung et al., 2022), and AI lawyer robots (Xu et al., 2022). The result suggests that perceptions of perceived ease of use do not necessarily lead to an increase in trust in video news.

A possible explanation for this outcome is linked to a lack of brand identity in the experiment. Brand reputation exerts a direct influence on users' perceived meaning, even more so in uncertain technological environments (Morgan-Thomas & Veloutsou, 2013), including online environments (Vaccari & Chadwick, 2020). In journalism, this sense of brand identity is translated into the media broadcast channel or the media author (Kim & Kim, 2020; Thurman et al., 2018; Túñez-López et al., 2020). This study counted on an online experiment that identified neither any brand (broadcast channel) nor any news author. The combination of these two factors might have negatively influenced perceptions of ease of use.

Additionally, user experience with the system proved to be a fundamental factor in defining the users' perceived ease of use (Liu et al., 2022; Venkatesh & Bala, 2008). The online experiment carried out in this investigation might have been ineffective because it was not able to reproduce the complete video system experience for participants, that is, system interactions such as switching videos, browsing, or finding related content. Similar behaviors were also verified in a study with automated vehicles (Zhang et al., 2019) that was not able to replicate the actual user experience with the technology.

In conclusion, Hypothesis 6 is rejected, suggesting that perceived ease of use is not an antecedent of trust in video news. With regards to the results of Hypothesis 6a, they will be addressed in the subsequent paragraphs.

5.7. Perceived usefulness and trust

Perceived usefulness proved to impact trust. According to the results, perceived usefulness → trust ($\beta = 0.652$; $t = 15.618$; $p = 0.000$), and Hypothesis 7 is accepted as suggested by the literature (Flavián et al., 2006; Liu & Tao, 2022; Roca et al., 2009; Xu et al., 2022; Zhang, 2010; Zhang et al., 2019). Hence, perceived usefulness is capable of influencing the user's trust in video news.

In contrast to perceived ease of use, perceived usefulness proved to be an antecedent of trust in video news. The relationship between perceived ease of use and perceived usefulness proved to be strong in video news, according to the results obtained.

Thus, Hypothesis 7 is accepted, concluding that perceived usefulness is an antecedent of trust in video news.

5.8. Multigroup analysis

Hypotheses H6a and H7a intend to compare results for those who have experienced AI-generated personalized video news (Group 1) and those who have watched human-generated content (Group 2). The multigroup analysis reveals that there are no significant differences between the groups in terms of the relationships perceived ease of use → trust ($\beta AI = 0.014$; $\beta Human = 0.045$; permutation p-value = 0.745) and perceived usefulness → trust ($\beta AI = 0.708$; $\beta Human = 0.581$; permutation p-value = 0.142).

These results support H6a and H7a, which defend similar effects on trust in AI-generated personalized video news and human-generated video news respectively through perceived ease of use (H6a) and perceived usefulness (H7a). Both hypotheses consider that both the determinant effect of visual appeal (Pegnate & Sarathy, 2017) and the possibility of resembling human interactions were enough to provide similar experiences and consequently comparable outcomes on trust in human-generated video news and AI-generated personalized video news (Han & Yang, 2018; Hsieh & Lee, 2021).

In H6a (perceived ease of use → trust), users' perceptions of how easy the technology is to operate do not seem to influence trust in video news, both in AI-generated personalized video news and in human-generated video news. No differences are found in the results of Groups 1 and 2. Hence, results show that trust was not an outcome of the system's perceived ease of use for those who have experienced AI-generated personalized video news or for those who have watched human-generated content. H6a is supported.

In H7a (perceived usefulness → trust), users' trust was highly affected by the perceived convenience of video news, both in AI-generated personalized news and human-generated news. Regardless of the type of news, both groups perceived video news as useful content, which directly influenced their trust. Perceived usefulness proves to be a common antecedent of trust in AI-generated personalized news and in human-generated news. Consequently, H7a is also supported.

The results of H6a and H7a are comparable to the findings that have been explored in the automated journalism literature. Users have presented similar levels of trust in articles generated by humans and by AI (Clerwall, 2014; Graefe et al., 2017; van der Kaa & Krahmer, 2014). Likewise, the results of the present experiment highlight this outcome in video news. This might be an indication that AI services are gradually becoming similar to human services. Reactions like the one registered regarding video news indicate that users are already perceiving that AI is able to provide services that thus far had only been performed by humans, including journalism. Similarities between human and AI content have proved to be strong enough to develop analogous levels of users' trust in both services.

In conclusion, trust in AI-generated personalized video news and human-generated video news tends to be a result of users' perceived usefulness and not their perceived ease of use. Similar levels of trust are recorded for both studied groups.

Table 5.1

Summary of hypotheses tested

Hypothesis	Path	Original Sample (O)	T-Statistics	P-value	Outcome
H1	E→U	0.354	6.207	0.000	Supported
H2	PI→U	0.240	3.985	0.000	Supported
H3	SA→U	0.095	1.607	0.108	Not supported
H4	MR→E	0.232	4.406	0.000	Supported
H5	MR→U	0.112	1.744	0.081	Not supported
H6	E→T	0.024	0.486	0.627	Not supported
H7	U→T	0.651	15.618	0.000	Supported
		β_{AI}	β_{Human}	P-value	
H6a	E→T	0.014	0.045	0.745	Supported
H7a	U→T	0.708	0.581	0.142	Supported

Note: Hypotheses, results (path coefficients, t-values, p-values) and outcomes (supported/not supported).

CHAPTER 6

Conclusion

The last part of this investigation aims to reflect upon the research progress and provide a good summary of the results obtained. The present section is divided into two subsections. The first one focuses on reassessing the research aim and its objectives, highlighting the investigation's main contributions. The second subsection seeks to summarize the limitations of this dissertation and the recommendations for future research.

6.1. Research aims and goals

This dissertation has aimed to investigate the levels of trust that users have in AI-generated personalized video news. To this end, three objectives were defined as follows:

1) To define trust in the context of this research, based on recent literature.
2) To develop a conceptual model capable of identifying the main variables that influence trust.
3) To compare levels of trust among those who have experienced AI-generated personalized video news and those who have watched human-generated video news.

With continuous technological development, companies are relying more and more on technology to provide personalized services to their customers (Alimamy & Gnoth, 2022). Organizations are increasingly co-creating value by incorporating the collaboration of customers into the process of value creation (Peltier et al., 2020). OTT services, in particular, have been combining AI with customer participation to create unique personalized experiences for their users. In view of evolving technology, more research is needed to understand the implications of AI in various dimensions. Therefore, the present investigation has focused on measuring levels of trust in AI-generated personalized video news.

The first objective attempted to define trust in a single definition in the light of the investigation. Trust is a very complex concept with a significant variety of definitions. Depending on the area and field of study, the interpretation of what is meant by trust can be subject to striking differences. In management, definitions tend to be imported from psychology, including those from Rotter (1967) and from Doney and Cannon (1997), which form the basis of this research: Trust is identified as the extent to which news consumers perceive video news as credible, reliable, and trustworthy.

The second objective is related to the proposed conceptual model. The goal was to develop a framework capable of identifying and relating the core variables pointed out by the literature. The TAM (Davis et al., 1989) is the pillar of the developed conceptual model due to its robustness, parsimony, and power. While TAM's simplicity in its variables is its main strength, it can also be its main weakness (Venkatesh, 2000). Thus, extensions and alternative models have also been proposed to add, identify, and consider other variables that were not included in the original model. Hence, the idea behind the proposed theoretical framework was to consider TAM's main variables (perceived usefulness and perceived ease of use) and to add four other constructs: perceived intelligence (Bartneck et al., 2009), social attraction (McCroskey & McCain, 1974; McLean et al., 2021), media richness (Lee et al., 2007), and trust (Gefen, 2000). The combination of these six constructs was sufficient to develop a unique conceptual model capable of relating the main variables highlighted by the literature. The results show that the conceptual model is free of common method variance and that both the outer and the inner models are consistent and reliable. The conceptual model can be considered an important contribution to this investigation.

The third and last objective was to compare levels of trust among those who have experienced AI-generated personalized video news and those who have watched human-generated video news. So far, the current stage of AI technology is not sufficient to supply a strong literature background on that particular topic, considering that AI technology is still under development. According to Huang and Rust (2018), the current technology is still in Stage 4 (analytical intelligence), which is the form of AI widely used by OTT video streaming platforms. Context awareness, which is the form of intelligence that would be used in AI-generated personalized video news by providing a context-specific response, is still to be developed (Davenport et al., 2020). Nevertheless, the experiment conducted in this investigation attempts to reproduce this potential technology by considering the current technological tendencies and predictions (Graefe et al., 2018; Linden, 2017; Thorne, 2020). The results evidence that there was no significant distinction in trust between those who have experienced AI-generated personalized video news and those who have watched human-generated video news.

These three objectives were determinant in guiding and achieving the aim of this investigation, contributing to the current gap in the literature. Up to this point, literature had mainly focused on research engines and filtering mechanisms (Darvishy et al., 2020; Haim et al., 2017; Lin et al., 2014; Manoharan & Senthilkumar, 2020; Wang, 2019; Wieland et al., 2021), news aggregators (Haim et al., 2019; Kwak et al., 2021), and the impact of news personalization on audiences (Merten, 2021; Swart, 2021; Thurman et al., 2019). The continuous development of AI technology requires further research into these areas to properly understand their various implications. AI-generated video news in particular is considered to be a viable technology for the future (Wang et al., 2022). Thus, deepening understanding in this area is indispensable, especially in the light of future technological developments.

Besides the three achieved goals, an interesting outcome of the research is the fact that results have shown similar levels of confidence among those who have experienced AI-generated personalized video news in comparison to those who have watched human-generated video news. This suggests that AI services are already able to provide services that previously were only performed by human beings. Results confirm that AI-generated content, namely personalized video news services, can be potentially trustworthy to users.

This discovery might be an interesting beginning for companies, private entities, and institutions, which could potentially invest in this kind of technology, and for researchers, who could and should extend the investigation.

6.2. Limitations and recommendations for future research

Despite the contributions of the research, this investigation also has some limitations, and relevant topics could be analyzed differently, either more deeply or through other lenses.

In terms of limitations, the research presents a constraint in terms of the sample. According to the research methodology, the convenience sample was used due to its easiness of obtaining responses. Hence, the method has demographic consequences for the sample, given that some of the respondents are within the network of the organizer. The responses obtained show a larger number of people aged between 20 and 29 years (63.1% of the total population), who are naturally more connected to the mediums used to spread the questionnaires than older people, who did not have a significant representation: Less than 1% of respondents were older than 70 years old. These figures may also reflect the limits of the experiment, which was restricted to those who were literate, either in English or in Portuguese; had Internet access; could use Google Forms; and consented to participate in the experiment. As an example, an elderly person who was unable to access or use the Google Forms technology could not be included in the sample of the experiment.

Another limitation is related to the measurement of trust. As already mentioned, trust is a complex construct with functional qualities (accuracy of information, functionality, usefulness) and non-functional qualities (emotions, feelings, user satisfaction; Balakrishnan & Dwivedi, 2021b; Shin, 2021a; Wirtz et al., 2018). This research only focuses on the functional qualities of trust, more precisely, on the impact generated by perceived usefulness and perceived ease of use on trust. Although important, non-functional elements were neither included in the conceptual model nor assessed in the experiment. This investigation only targeted functional elements of trust.

Based on the results obtained, it was discussed whether the experiment of this investigation reproduced a rich system experience for the two studied groups or not. User experience of the system proved to be a crucial determinant in defining perceived ease of use and trust (Liu et al., 2022; Venkatesh & Bala, 2008). The insignificant relationship between perceived ease of use and trust seems to be contrary to the literature, implying that the experiment may have impacted the relationship. The impact of the news content and information overload contained in the experiment may also have affected perceptions of media richness and social attraction in perceived usefulness. It would be extremely important to improve the overall user experience in the experiment so as to explore the effects of system experience on media richness, social attraction, perceived ease of use, perceived usefulness, and trust.

The conceptual framework proposed in this study proved to be reliable and to have a good fit. The results and the various tests have shown the reliability and credibility of the designed conceptual model. Nevertheless, it would be interesting to verify the correlation between media richness and social attraction, which seems to be relevant (Hsieh & Lee, 2021; Zhao et al., 2020).

Based on the literature analysis and interpretation, it was possible to identify that part of the literature considers trust to be an antecedent of perceived ease of use and perceived usefulness

(Ghazizadeh et al, 2012; Ha & Stoel, 2009; Huang et al., 2022c; Liu & Tao, 2022; Ortega & Román González, 2011; Pavlou, 2003; Yang et al., 2015). In contrast, taking into consideration another part of the literature, the present research considers trust as a construct that is *influenced* by perceived ease of use and perceived usefulness (Acharya & Mekker, 2022; Flavián et al., 2006; Roca et al., 2009: Xu et al., 2022; Zhang, 2010; Zhang et al., 2019). Depending on the scope of analysis, trust could be positioned either *before* perceived usefulness and perceived ease of use, as a construct that influences both, or *after* perceived usefulness and perceived ease of use, as a variable that is influenced by both. Therefore, it might also be interesting to investigate the effects of trust in terms of these variables, positioning the construct before perceived usefulness and perceived ease of use.

Furthermore, the proposed conceptual model was intended to measure trust by reclaiming the two most important constructs of the TAM, namely perceived usefulness and perceived ease of use (Davis et al., 1989). Nonetheless, the present research does not assess the technology acceptance of AI-generated personalized news technology. Therefore, it would still be relevant to evaluate technology acceptance either through the TAM framework or its extensions (Davis & Venkatesh, 2000; Venkatesh, 2000; Venkatesh & Bala, 2008) or even by using the UTAUT (Venkatesh et al., 2003) and the UTAUT 2 (Venkatesh et al., 2012).

In conclusion, the present research has investigated the levels of trust that users potentially have in AI-generated personalized video news in comparison to human-generated video news. This study is just a small step in the research on the possibility of generating content through AI, personalized video news included. The ideas, concepts, evaluations, and conceptual model contained in this investigation can certainly be extended for future research.

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Annexes

A. Tables and figures

Table 1

Initial results - constructs, indicators, and reliability indicators

Construct (Latent Variable)	Indicator	Outer Loading	Cronbach's Alpha (α)	Composite Reliability (CR)	Average Variance Extracted (AVE)
Perceived ease of use	E1	0.738	0.874	0.895	0.609
	E2	0.795			
	E3	0.759			
	E4	0.790			
	E5	0.846			
	E6	0.750			
Media richness	*MR1*	*0.654*	0.844	0.845	0.477
	MR2	*0.701*			
	MR3	0.704			
	MR4	0.690			
	MR5	0.744			
	MR6	0.720			
	MR7	0.660			
	MR8	*0.646*			
Perceived intelligence	PI1	0.719	0.806	0.825	0.564
	PI2	0.821			
	PI3	0.745			
	PI4	0.807			
	PI5	*0.651*			
Perceived usefulness	U1	0.752	0.896	0.898	0.616
	U2	0.835			
	U3	0.785			
	U4	0.825			
	U5	0.786			
	U6	0.748			
	U7	0.757			
Social attraction	SA1	0.699	0.576	0.749	0.277
	SA2	0.824			
	SA3	*-0.007*			
	SA4	*0.248*			
	SA5	*0.525*			
	SA6	0.678			

	SA7	*0.611*			
	SA8	*0.051*			
	SA9	*0.189*			
	SA10	*0.631*			
Trust	T1	0.825	0.859	0.868	0.782
	T2	0.928			
	T3	0.896			

Note: MR2 was not subject to removal thanks to its original value 0.701 above the accepted minimum. However, during the removal process, the deletion of MR1 and MR8 is sufficient to increase loadings that were originally below MR2 (such as MR4 and MR7) and to decrease the value of MR2 to 0.669, justifying its removal.

Table 2

Composite reliability and validity results

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	AVE
E	0.874	0.894	0.903	0.609
MR	0.836	0.840	0.884	0.604
PI	0.799	0.818	0.868	0.623
U	0.896	0.899	0.918	0.616
SA	0.763	0.844	0.860	0.674
T	0.859	0.868	0.915	0.782

Table 3

Cross loadings

	E	MR	PI	U	SA	T
E1	0.743	0.185	0.145	0.266	0.002	0.212
E2	0.795	0.100	0.061	0.292	0.007	0.248
E3	0.759	0.121	0.058	0.213	0.032	0.167
E4	0.789	0.129	0.152	0.312	0.144	0.220
E5	0.846	0.235	0.253	0.429	0.106	0.248
E6	0.748	0.249	0.233	0.441	0.150	0.307
MR3	0.142	0.791	0.355	0.227	0.276	0.128
MR4	0.195	0.747	0.379	0.272	0.260	0.172
MR5	0.160	0.748	0.274	0.251	0.237	0.150
MR6	0.222	0.826	0.348	0.269	0.228	0.158
MR7	0.168	0.771	0.244	0.222	0.197	0.088
PI1	0.173	0.337	0.727	0.245	0.377	0.206

PI2	0.136	0.301	0.865	0.360	0.354	0.328
PI3	0.206	0.280	0.752	0.285	0.342	0.267
PI4	0.169	0.393	0.806	0.361	0.347	0.362
U1	0.328	0.303	0.365	0.753	0.258	0.562
U2	0.446	0.234	0.421	0.837	0.200	0.541
U3	0.348	0.268	0.339	0.787	0.198	0.526
U4	0.347	0.221	0.341	0.826	0.173	0.535
U5	0.294	0.229	0.274	0.785	0.208	0.506
U6	0.274	0.216	0.174	0.745	0.223	0.488
U7	0.362	0.296	0.261	0.755	0.247	0.464
SA1	0.053	0.183	0.390	0.162	0.766	0.264
SA2	0.086	0.270	0.424	0.289	0.907	0.305
SA6	0.125	0.301	0.277	0.193	0.783	0.184
T1	0.269	0.129	0.262	0.530	0.178	0.825
T2	0.302	0.175	0.376	0.628	0.331	0.928
T3	0.252	0.177	0.356	0.592	0.299	0.896

Table 4

VIF – outer model

	VIF
E1	1.836
E2	2.175
E3	2.234
E4	2.102
E5	2.333
E6	1.657
MR3	1.873
MR4	1.536
MR5	1.563
MR6	1.961
MR7	1.805
PI1	1.533
PI2	2.011
PI3	1.510
PI4	1.599
U1	2.008
U2	2.550
U3	2.335
U4	2.637
U5	2.379
U6	2.786
U7	2.592
SA1	1.542
SA2	1.780
SA6	1.465
T1	1.770
T2	3.114

T3	2.662

Table 5

VIF – inner model

	E	MR	PI	U	SA	T
E				1.076		1.241
MR	1.000			1.270		
PI				1.418		
U						1.241
SA				1.276		
T						

Table 6

Model fitness

	Saturated model	Estimated model
SRMR	0.067	0.071
d_ULS	1.809	2.066
d_G	0.607	0.622
Chi-square	1080.099	1084.424
NFI	0.771	0.771

Table 7

R-Square

	R-square	R-square adjusted
E	0.054	0.051
U	0.314	0.305
T	0.438	0.434

Table 8

LV Prediction Summary

	Q^2predict	RMSE	MAE
E	0.041	0.986	0.790
U	0.172	0.918	0.697
T	0.117	0.945	0.775

Figure 1

Common Method Variance model – Vertical collinearity assessment

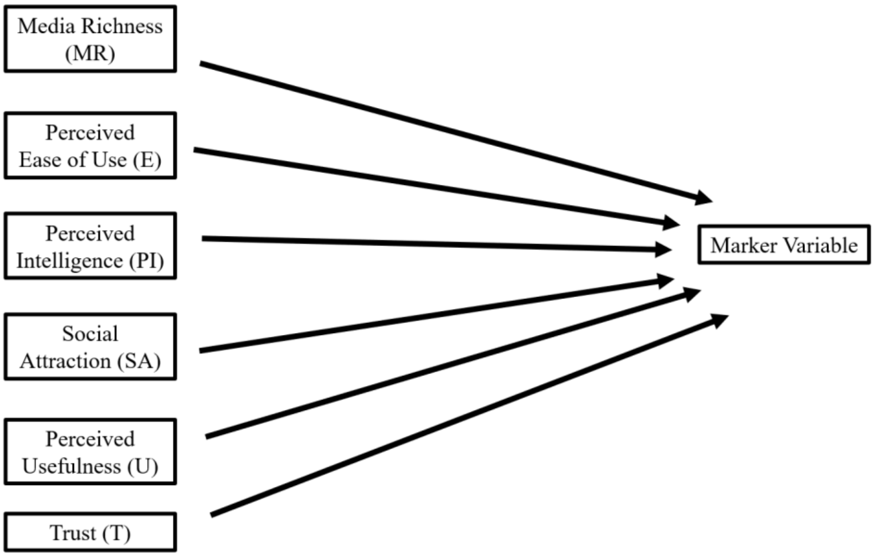

Table 9

Common method variance model – vertical collinearity assessment results

	E	MR	MV	PI	U	SA	T
E			1.236				
MR			1.012				
MV							
PI			1.359				
U			1.987				
SA			1.271				
T			1.797				