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AVATAR MARKETING:

THE ROLE OF GENDER AND SERVICE TYPE ON PERCEIVED COMPETENCE AND INFORMATION DISCLOSURE

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1. Introduction

1.1 Artificial Intelligence

Artificial intelligence (AI) can be defined as a system that uses technology to evaluate service scenarios in real-time while using data gathered from digital and/or physical sources to offer alternatives, recommendations, suggestions, and tailored solutions to customer requests or problems, even those that are extremely complex (Xu et al., 2020).

AI can also be defined as *"the use of computational machines to emulate capabilities intrinsic to humans, such as performing physical or mechanical tasks, thinking, and feeling"* (Huang & Rust, 2021, p. 31).

In the 1950s, when the first computers were invented, artificial intelligence (AI) emerged almost simultaneously. However, in recent years, AI has accelerated due to quick improvements in computer power, a variety of technologies (such as computer vision, machine learning, and natural language processing), and an abundance of data that can be used to train algorithms (Bornet et al., 2021).

To learn from the patterns and properties of the data they study, artificial intelligence (AI) systems combine enormous data sets with clever, iterative processing methods. Every time an AI system runs a data processing cycle, it tests, measures, and improves its performance.

The fact that AI never requires a break allows it to complete hundreds, thousands, or even millions of tasks very quickly while also picking up new skills very quickly in whatever it is trained to accomplish.

To do this, artificial intelligence uses fundamental tools, such as machine learning and deep learning.

Machine learning is a particular application of AI that enables systems or computer programs to automatically comprehend and provide outcomes based on experience.

The ML algorithm combines a variety of statistical techniques and works with input data to enable the AI to find patterns in the data and hence improve task results.

Deep learning is a subdivision of machine learning that makes use of artificial neural networks that resemble the biological neural networks of the human brain. This enables artificial intelligence to learn and develop as it consumes data and derives conclusions or outcomes.

In addition to machine learning and deep learning, AI systems need cognitive computing capabilities, robotics, computer vision, and language processing so that computer models can replicate how the human brain functions when doing a difficult task (Forbes, 2023).

However, to understand how AI works, it is important to know that artificial intelligence is more than just a single computer program or application. Rather, AI refers to a whole field of study or research whose objective is to create a computer system that can simulate human behavior and employ human-like reasoning to solve challenging problems. In the field of artificial intelligence science, a distinction is made between 'narrow' and 'general' artificial intelligence (Accenture, 2023).

Most AI applications that we experience in everyday life fall under the concept of 'narrow' (or weak) artificial intelligence, which works in a constrained environment and simulates human intelligence when applied to a clearly defined task (e.g., Alexa, conversational bots, Netflix recommendations, and spam filters). Narrow AI

is frequently concentrated on effectively completing a specific task. Even though these machines may appear clever, they have a lot more restrictions and limits than even the most primitive human intellect.
Contrarily, 'general' (or strong) artificial intelligence is a machine that can solve issues for which it has never been educated, just like a human being. Strong AI, compared to weak AI, represents an unrealized machine with a complete set of cognitive abilities and a wide range of potential applications.
Another way by which AI can be subdivided involves its classification into four groups, based on the kinds and degrees of difficulty of the tasks a system is capable of (Google, 2023), which correspond to the stages of AI development. They are:

1. *Reactive machines*: A reactive machine is only able to use its intelligence to detect and respond to the environment in front of it; this type of AI is memoryless and hence unable to use the past to inform current judgments (e.g., Deep Blue and AlphaGo).

2. *Limited memory*: A limited-memory AI can preserve past data and forecasts when gathering information and considering options; to create one, one must either continuously train a model to interpret and apply fresh data or provide an AI environment in which models may be taught and regenerated automatically.

3. *Theory of mind*: This is only a theoretical idea because we do not yet possess the technological and scientific advancements necessary to develop a type of artificial intelligence that can comprehend how people, animals, and other machines perceive and make choices via self-reflection and determination, as well as using this knowledge to make its own decisions.

4. *Self-awareness*: Once the theory of mind is achieved, the next step will be to make the AI self-aware, which implies that this type of AI will possess a human-level conscience and be aware of both its own presence and other people's presence and emotional states.

Within the report “Artificial Intelligence: in-depth market analysis” (2023), Statista reports on a further way of classifying artificial intelligence, which makes a distinction between:

- *Machine learning*: Learning algorithms (such as supervised learning, unsupervised learning, and reinforcement learning) that enable the analysis of vast amounts of complex data to find patterns, make predictions, and make changes.

- *Robotics*: A field of technology whose primary fields include Soft Robotics, Swarm Robotics, Haptic Robotics, Humanoid Robots, and Serpentine Robots and which is focused on creating and training robots to interact with people and the rest of the world in predictable ways.

- *Artificial Neural Networks* (ANNs): algorithms that imitate the operation of the neocortex region of the human brain, which is where thinking takes place and they can be divided into Deep Learning, Recurrent Neural Networks, and Convolutional Neural Networks.

Today, AI is applied in an expanding variety of scenarios and technologies outside of just computer-related industries. Smartphones, recommendation engines, and customer service are a few of these (Makridakis, 2017; Wirtz et al., 2018; Zhang et al., 2021). They also play increasingly important roles in professions that were once assumed to require a high level of intellectual ability, such as journalism (Carlson, 2015), the arts (Quackenbush, 2018), music creation (Marshall, 2018), and marketing (Sterne, 2017).

According to SAS and Gartner, every industry has a high demand for AI capabilities, including those for systems that may be used for automation, learning, legal aid, risk alerting, and research. To give examples, AI applications can be used in the *healthcare* industry to read X-rays and give customized treatment; in *manufacturing*, AI can use recurring networks to assess factory IoT data from connected equipment to forecast predicted load and demand; in *life sciences*, the benefits include protecting the security of medications and accelerating the release of novel treatments; in *banking*, AI approaches can be applied to detect potentially fraudulent transactions, implement quick and precise credit rating, and automate routine data management chores; in the *public sector*, AI can improve the efficiency and effectiveness of programs, such as supporting national defence with mission readiness and predictive maintenance.

Some typical applications of AI that, as noted by Forbes (2023), we utilize daily are visually shown in Table I.

Table I. Forms of artificial intelligence we use today (Forbes, 2023)

Digital assistants (e.g., Siri)	**Google Maps**	**Live chatbot**	**Self-driving cars**
			
Interactive videogames	**Wearable sensors & devices**	**Medical biosensors**	**Robotic advisors for stock trading**
			

1.2 AI Recommendation Systems

Recommender systems are described as systems in Resnick and Varian's article (1997) as ones in which *"people provide recommendations as input, which the system then aggregates and directs to the appropriate recipients"* (p. 56). This definition, which presents recommendation systems as supporting collaboration between users (Burke, Felfernig & Göker, 2011), was later broadened to encompass all systems that provide recommendations regardless of how they are made: *"any system that produces individualized recommendations as output or has the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options"* (Burke, 2002; p. 331).

In light of what has just been reported, it is, therefore, possible to say that a recommendation system is customized in the sense that the suggestions are made to enhance the user's experience rather than to represent the consensus of one group for everyone and to assist the user in making choices from a range of options. Since we expect search engines and other information retrieval tools to provide the same set of relevant results for a given query regardless of who is searching, recommender systems' personalization sets them apart from these tools.

Many recommendation systems keep profiles of user activity (long- or short-term) or expressed preferences to tailor recommendations (Schafer et al., 2007), whereas other systems personalize results through conversational engagement (McGinty & Reilly, 2011).

Each recommendation system draws on one or more knowledge sources to perform its task and it is precisely based on the knowledge sources they use that Felfernig and Burke (2008) classify them. These two authors make a distinction between:

- *Social knowledge* based on users in general (opinions, behavior, demographics, context)
- *Individual knowledge* of the specific individual for whom recommendations are being sought (behavior, opinions, demographics, needs for the query, restrictions, preferences, context)
- *Content knowledge* of the recommended articles, which can range from straightforward lists of qualities to more intricate ontological information, allows the system to consider how an item might satisfy a user's demands.

However, classifications of recommendation techniques are varied (Resnick & Varian, 1997; Schafer, Konstan & Riedl, 1999; Terveen & Hill, 2001).

Considering that recommendation systems have (i) background data, i.e. the knowledge the system has before the recommendation process, (ii) input data, i.e. the knowledge the user must communicate to the system in order for it to generate a recommendation, and (iii) an algorithm that integrates input and background information to provide suggestions, the various recommendation methods can be distinguished as illustrated in Table II, which assumes that I is the collection of things on which suggestions can be generated, U is the set of users whose tastes are understood, u is the user for whom suggestions are to be produced, and i represents the item for which u's preference must be predicted.

Table II - Recommendation techniques (Burke, 2002)

Technique	Background	Input	Process
Collaborative	Ratings from **U** of items in **I**.	Ratings from **u** of items in **I**.	Identify users in **U** similar to **u**, and extrapolate from their ratings of **i**.
Content-based	Features of items in **I**	**u**'s ratings of items in **I**	Generate a classifier that fits **u**'s rating behavior and use it on **i**.
Demographic	Demographic information about **U** and their ratings of items in **I**.	Demographic information about **u**.	Identify users that are demographically similar to **u**, and extrapolate from their ratings of **i**.
Utility-based	Features of items in **I**.	A utility function over items in **I** that describes **u**'s preferences.	Apply the function to the items and determine **i**'s rank.
Knowledge-based	Features of items in **I**. Knowledge of how these items meet a user's needs.	A description of **u**'s needs or interests.	Infer a match between **i** and **u**'s need.

To produce a recommendation, AI recommendation systems mainly use content-based filtering and collaborative filtering (Namjun et al., 2019).

When a user selects an article, content-based filtering analyzes a set of discrete traits to create a filter and suggests additional articles with the same qualities (Pazzani, 1999) while collaborative filtering creates a filter by analyzing a user's past behavior, such as clicks, purchases, and evaluations, along with comparable decisions made by other users, to construct a list of items in which the user could be interested (Schafer et al., 2007).

Collaborative techniques have the advantage of being completely independent from any machine-readable representation of the products to be advised, making them appropriate for recommending complex items like music and movies where differences in taste account for a large portion of the variation in preferences.

There are many types of models in collaborative recommender systems, and according to Forbes (2019) there are three that are worthy of further investigation:

- *Popularity*: views are recommended based on the frequency with which they are viewed.

- *Neighbourhood modelling*: recommendations are made by considering a cohort of people similar to the particular user.

- *Latent factor modelling*: objects accessed are defined by a set of attributes of the people using those objects; each attribute is assigned weights based on its importance and then analyses are performed to see which other objects/displays are the closest match for the displayed element.

When a product is relatively new and nobody has tried it yet, collaborative filtering is not of much use, whereas content filtering can be used to decide whether it is close enough to what a customer uses to recommend it to that person. Conversely, when a new user views a piece of content but does not have a rich enough history, through the collaborative approach the recommendation system can extend what other users have viewed subsequently until there is enough usage history to start including content filtering. Considering the complementarity between these two methods, it can be argued that content-based filtering and collaborative filtering can operate independently, simultaneously, and in combination (Koren, Bell & Volinsky, 2009).

Demographic recommendation systems, on the other hand, aim to categorize users according to personal attributes and provide recommendations according to demographic groups. Although demographic procedures and collaborative techniques both build person-to-person connections, they do so using distinct types of information.

A demographic approach has the advantage that it does not call for the kind of history of user assessments required by content-based techniques and collaborative techniques.

Utility- and knowledge-based recommenders, on the other hand, base their recommendations on an evaluation of how well the user's needs and the range of available options match up. They do not make attempts to create long-term generalizations regarding the users.

Utility-based recommenders base their recommendations on a calculation of the usefulness of each item for the consumer. This approach has the advantage that it can take into account non-product attributes, such as the dependability of the seller and the availability of the product, in the utility calculation, making it possible, for instance, to trade price for delivery time for a user with an immediate need.

The goal of knowledge-based recommendations is to make recommendations for products based on assumptions about the consumer's requirements and tastes. Though all recommendation methods can be characterized as inference, knowledge-based approaches are unique because they have functional knowledge, i.e., knowledge about how a specific item satisfies a specific user need, and can therefore reason about the connection between a need and a potential suggestion.

Although recommender systems are incredibly helpful tools that save users time by proposing content they were unaware of, other researchers contend that their use can negatively impact users' perceptions (Namjun et al., 2019). According to Eli Pariser (2011), a website algorithm decides what content a user will view depending on information that has already been gathered about them, such as their location, past actions, and search history. Users are thus isolated in their own ideological bubbles and cut off from information that contradicts their beliefs. This concept is similar to Echo Chambers, whereby individuals exclusively consume items that support their ideology as a psychological defence mechanism to protect their beliefs and value systems from information that might challenge them (Cass Sunstein, 2001).

1.3 The Anthropomorphization of AI

The first to provide a definition of anthropomorphism was Guthrie Steward (1995), an anthropologist who defined it as the tendency to see the human in non-human forms and occurrences.

According to Epley et al. (2007), anthropomorphism occurs when a non-human agent or inanimate object is given physical or non-physical traits, emotions, behavior, attributes, and human-like features.

Anthropomorphism is defined and measured differently in several research areas, including marketing, social cognition, marketing, human-computer interaction, and human-robot interaction (Moussawi & Koufaris, 2019).

Previous research has examined aspects like human resemblance and sociability (Kiesler & Goetz, 2002a, 2002b; Kiesler et al., 2008; Powers & Kiesler, 2006); motion, fakeness, artificiality, consciousness of robots (Bartneck et al., 2007, 2009); emotions, attributions of intentions, mind, free will, and consciousness (Epley et al., 2007; Waytz et al., 2010; Waytz et al., 2014); or attributes that are typically or uniquely human (Haslam et al., 2008).

According to Haslam (2008), humanness is to be understood as traits or qualities that are specifically human and that other animals do not have, such as higher cognition, culture, and social learning, or traits that are typically human and thus inherent to human nature and that we may have in common with animals.

In line with this, we define perceived anthropomorphism as the extent to which users identify the agent as a person based on both typically and uniquely human traits, such as looseness, respect, or fun (uniquely human attributes), and being caring, amiable, or happy (characteristics of human nature) (Moussawi & Koufaris, 2019).

Anthropomorphism appears to be an innate human tendency, well documented in human history for a long time. Drawings dating back some 30,000 years in fact represent animals with human-like forms (Dalton, 2003).

According to Epley et al. (2007), the urge to make non-human agents' behavior and intents easier to understand and explain is what drives people to anthropomorphize them. When logical understanding of the non-human agency is absent, anthropomorphism is applied to a non-human agent or entity. In this kind of situation, the desire to communicate with and comprehend the non-human being may motivate the use of anthropocentric knowledge.

As stated by Epley et al. (2007), anthropomorphism generally has two distinct forms. The first form (Zhu & Chang, 2020) concerns the traits and appearance of non-human items that are similar to those of humans, for which anthropomorphism is an inductive inference process related to the observable traits or behavior of non-human objects (Kim & McGill, 2011). The other type of anthropomorphism gives human-like traits to non-human creatures, such as language usage (Choi et al., 2019), empathy (Leiten et al., 2013), and other communication skills (Murphy et al., 2019). These two types, though not entirely distinct, collaborate to affect customers' propensity to use particular goods or services.

The process of anthropomorphism's inductive inference is similar to cognitive biases like anchoring and overconfidence for which human agents use information about humans to make a judgment about a non-human agent because this type of information is the most readily available (Epley, 2004; Epley et al., 2007; Griffin

& Tversky, 1992). In addition, Epley et al. (2007) claim that individuals who lack the time or cognitive capacity to create an induction are more likely to form a final judgment that is affected by easily accessible anthropocentric knowledge.

To clarify the use of anthropomorphism, these authors developed a theory containing three essential factors that affect the likelihood that anthropomorphism would be used by humans.

They are:

- The *agent's knowledge* is a determining factor in explaining the behavior or characteristics of a non-human agent. A human agent is likely to base a decision on information that is easily accessible about human behavior or human qualities if they have little or no knowledge of a non-human agent.
  When a human agent learns more about the non-human agent, the knowledge gained should activate alternative structures of knowledge that compete with human knowledge, which would then result in an adjustment of the judgment concerning the non-human agent and a reduction in the probability and level of anthropomorphism.

- *Effectiveness in anthropomorphism* refers to a human agent's goal to comprehend and communicate with a non-human agent in an effective manner. It is derived from White's effectance motivation, which was first stated in 1959. The human agent seeks to comprehend the motivations behind the non-human agent's acts and to lessen ambiguity regarding the non-human agent's future behaviors by applying human features and attributing human goals to non-human agents. As a result, anthropomorphism assists human agents in maintaining control of a situation by lowering ambiguity and anxiety.

- *Sociality* refers to a person's need to interact with other people, and the sociality motivation is achieved when a social connection is made with a non-human agent.

In line with the tendency of humans to assign human-like features and feelings to lifeless or non-human objects from an early age (Derby, 1970; Lanier Jr. et al., 2013), consumer research and product marketing have found that anthropomorphism applied to product design results in higher levels of sympathy in humans (Aggarwal & McGill, 2007; Landwehr et al., 2011; Wen Wan et al., 2017).

For this reason, hardware and software engineers attempt to incorporate human characteristics and features into technology to help people interact with the system and grow familiar with its capabilities (Burgoon et al., 2000; Epley et al., 2007).

For instance, Landwehr et al. (2011) identified the considerable impact of mobile phones with designs that resemble a human face's eyes and mouth. Their findings suggest that by designing the design in a way that recalls human features, consumers are more likely to anthropomorphize, potentially leading to greater product appreciation.

Through anthropomorphization, interactions between humans and an inanimate object can similarly become human-human interactions, leading to attachment to the object and the satisfaction of a person's requirements for comfort, likeability, identity, and self-efficacy. (Wan & Chen, 2021).
According to Ki et al. (2020), Ramadan et al. (2020), and Hernandez-Ortega & Ferreira (2021), this type of psychological and emotional connection, or attachment, can also take the shape of unity, (perceived) friendship, or love.
Computers are among the inanimate items that are viewed by humans as having an anthropomorphic quality, according to Nass et al. (1996), who were among the first to make this observation. According to their study on the "computers are social actors" theory, when people engage with computers that are infused with human or social cues, they frequently use social heuristics. Social interaction with machines has revealed an unnatural attribution of human traits to machines, which not only results in socially acceptable behavior toward inanimate things, such as politeness (Nass et al. 1999) but also in sentimental and favorable reactions towards machines (Nass et al. 1996; De Melo et al. 2014).
As stated by Pfeuffer, Benlian, Gimpel, and Hinz (2019), the anthropomorphic design also appears to have positive effects on information technology and information systems.
The human-like voices of Apple's Siri or Google Assistant would be able to promote more trust and a stronger social connection between users and agents (Apple Inc. 2018; Google LLC 2018).
Similarly to this, simple visual clues are employed to boost the robot's credibility, such as the flashing eyes of Anki's home helper vector (Fig. I).

Fig. I - AI Robot Companion (Anki)

Historically, artificial intelligence has been viewed as being anthropomorphic. In fact, some of its algorithms employ biomimetic designs in an intentional effort to achieve a kind of digital isomorphism of the human brain, while others make use of more general learning techniques that are consistent with well-liked theories of cognitive science and social epistemology (Watson, 2019). We now speak of machines capable of thinking, learning, and inferring. The very term artificial intelligence prompts us to draw comparisons between our human ways of reasoning and the behavior of algorithms.
The ability of AI to mimic human cognitive processes and interactions offers anthropomorphic clues that drive users to regard them as similar to people and develop emotional attachments (Wan & Chen, 2021) and this also leads to a change in our perceptions of technology and its use (Kim & Im, 2023).

Given the ongoing development of AI and its intelligence levels, it is assumed that its capabilities, emotional and social skills, and its degree of humanization will increase even more (Hermann, 2022).

Applications of AI, such as chatbots, service robots, and intelligent personal/digital assistants (like Siri or Alexa), already have human morphology, names, and characteristics, such as the ability to recognize language and emotions (Huang & Rust, 2021; Ramadan et al., 2021; Wan & Chen, 2021).

Unique speech recognition, a welcoming appearance, and personalized user interfaces are some examples of AI developments (Haas et al., 2020).

The effect that anthropomorphism can have on customers' propensity to use it represents an important area of study in marketing literature.

Customers trust anthropomorphic AI service agents more than non-anthropomorphic ones, according to research by Waytz et al. (2010), and anthropomorphizing AI service agents, according to De Visser et al. (2017), improves customer interaction.

Similar findings were reached by Yuan and Dennis (2019), who looked into how specific anthropomorphic traits affect the willingness of clients to pay and came to similar results.

Numerous empirical examples of the beneficial impact of anthropomorphism on acceptability or willingness to use have been offered by other marketing research (Chandler & Schwarz, 2010; Landwehr et al., 2011). Anthropomorphism has gained attention in recent research as a potentially important aspect of conversational agents like chatbots (Mehta et al., 2022; Pizzi et al., 2021; Roy & Naidoo, 2021). According to Waytz et al. (2014), this suggests that human-like chatbots are more trustworthy than non-humanoid chatbots. Consumers' awareness of their social presence and, as a result, their purchase intention are increased by high levels of anthropomorphism (Han, 2021). Similar to this, chatbots that mimic human characteristics can boost customers' confidence in the service provider (De Visser et al., 2016; Seeger & Heinzl, 2018), which in turn enhances customers' readiness to divulge their personal information (Chang et al., 2017).

Most of the literature aimed at studying the effect that the anthropomorphization of service agents has on customer responses has mentioned human-robot interaction (HRI) as an important research area (Fan et al., 2020; Rosenthal-von Der Pütten & Krämer, 2014). Human-robot interaction (HRI) studies look at how people perceive machines that can interact with people and satisfy their emotional and social requirements (Fan et al., 2020). Most of these studies have suggested that people evaluate anthropomorphic products or service agents more positively than non-anthropomorphic ones (Gong, 2008). In the service industry, anthropomorphic customer service representatives have been demonstrated to increase customer trust and help them form bonds with the service (Cheng, 2018; Qiu et al., 2020). To accomplish their commercial objectives, many organizations anthropomorphize their products or service agents to imply particular brand attributes like familiarity, safety, reliability, and friendliness (Ambroise & Valette-Florence, 2010). The widespread consensus is that when service agents are created to be as humanistic as feasible, consumers' propensity to utilize them increases (Yang et al., 2022).

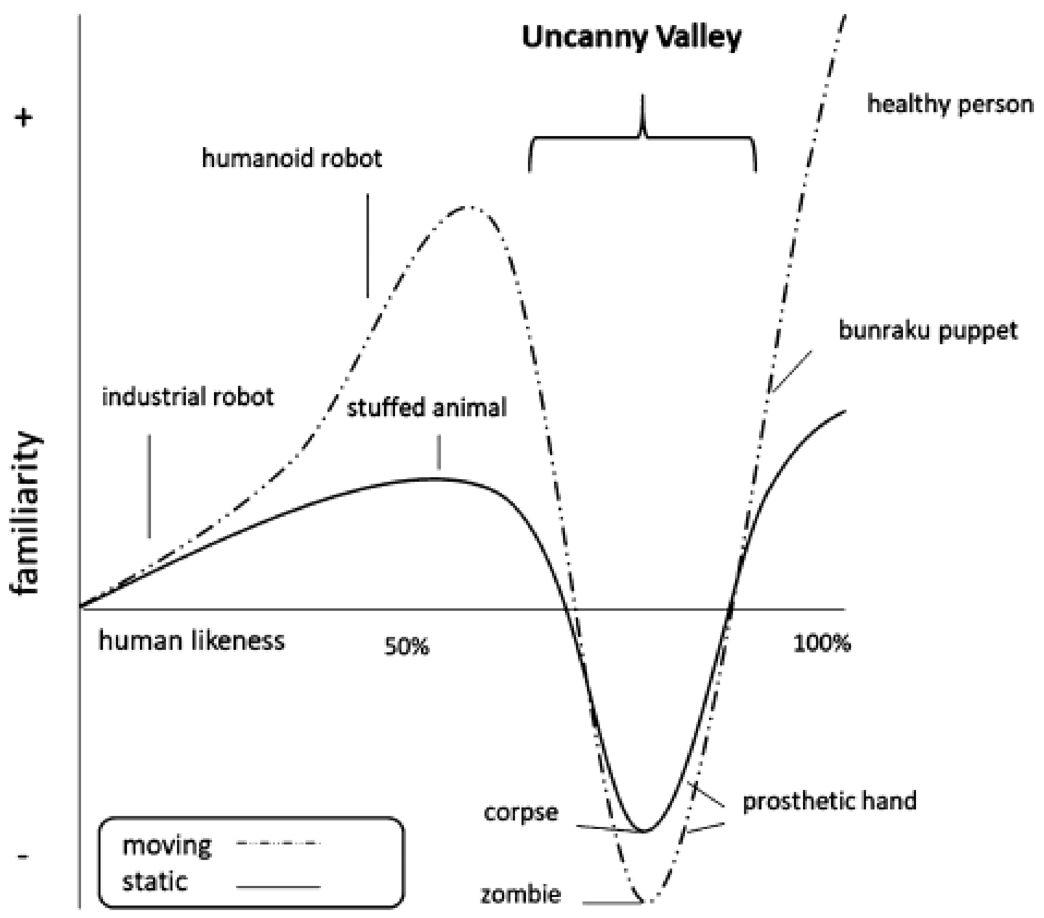
However, as stated by Zhu and Chang (2020), humans don't always favor interacting with anthropomorphic agents. Customers' willingness to employ the AI service agents is lowered as a result of the anthropomorphic design's tendency to inspire expectations that the agents cannot meet (Bartneck et al., 2010).

As postulated by the “Uncanny Valley” (Fig. II), above a certain threshold the degree of resemblance to humans could have a negative effect.

The concept of Uncanny Valley was first used by Mori to refer to the region of a graphic depicting an object that resembles a human being where the object's human resemblance becomes so strong that the human agent experiences disquiet instead of the initial high level of sympathy. The anthropomorphic design raises expectations that the anthropomorphic object cannot meet, which is the source of this unease.

The uncanny sense vanishes after the thing achieves the next level of human similarity and crosses the uncanny valley because it can then satisfy expectations and is seen as being highly human-like.

Fig. II - Uncanny Valley (Mori, 1970)



1.4 Avatars

Avatars are virtual characters that can be understood as anthropomorphic-looking digital beings that can interact and are controlled by a person or software as a result of advancements in computer technology (Miao et al., 2022).

The term 'avatar' derives from Indian mythology (from Sanskrit *avatāra*) and refers to the incarnation of a deity on earth (Holzwarth et al., 2006), specifically the god Vishnu and his ten incarnations (Garnier & Poncin, 2013).

Today, this term is used to refer to *"a pictorial representation of a human being in a chat environment"* (Bahorsky, Graber & Mason, 1998, p. 8) or *"a representation of the user as an animated character in virtual worlds"* (Loos, 2003, p. 17).

As a result of the lack of a universally agreed-upon definition of "avatars," scholars have used various terms to describe them interchangeably, including chatbots (Ho, Hancock, & Miner, 2018), automated shopping assistants (Al-Natour, Benbasat, & Cenfetelli, 2011), embodied conversational agents (Bickmore, Pfeifer & Jack, 2009; Lee & Choi, 2017; Schuetzler et al., 2018), virtual customer service agents (Verhagen et al., 2014), or virtual/digital assistants (Chattaraman et al., 2019; Freeman & Beaver, 2018).

Regarding the entity of control over the avatar, either a human operator or an automated computer program could be involved (Nowak & Fox, 2018). According to some, when control is entrusted to technology one speaks of an agent or bot, while when control is entrusted to humans one speaks of an avatar (Nowak & Fox, 2018). However, due to financial constraints, in current business practices, artificial intelligence seems to be the primary enabler of digital avatars. One aspect on which there is no general consensus is whether avatars should necessarily have an anthropomorphic look (Nowak & Fox, 2018). In academic research, an anthropomorphic or human-like look is cited as a prerequisite for the conceptual characterization of an avatar in 70% of the studies (Miao et al., 2022) and, in line with this, anthropomorphism would seem to give the avatar greater credibility and perceived competence by users (Westerman, Tamborini & Bowman, 2015).

Another requirement for talking about avatars is interactivity, i.e., the "extent to which individuals perceive that communication allows them to feel in control as if they can communicate synchronously and reciprocally with the communicator" (Chattaraman et al. 2019, p. 317). Avatar interactivity refers to their ability to interact bidirectionally, either verbally (voice) or non-verbally (animation, text). Previous studies have identified three aspects of interactivity: synchronization, bilateral interactions, and active user control, which refers to the user's capacity to take part in and shape communication (Liu & Shrum, 2002; Etemad-Sajadi, 2016).

Miao et al. (2022) created a typology of avatar design to help academics and managers identify the components that make an avatar more or less useful for achieving particular objectives, such as presenting product information or responding to client inquiries about the purchasing process, among others. According to these authors, all design elements influence the form realism and behavioral realism of avatars. 'Form realism' describes how closely an avatar resembles a human being, whereas 'behavioral realism' describes how closely the avatar behaves like a human in the physical world (Bailenson et al., 2008; Blascovich et al., 2002; Fox et al., 2015). Both form and behavioral realism are linked to better avatar usefulness in most circumstances

(Garau et al., 2003; Yee, Bailenson & Rickertsen, 2007; Kang, Watt & Ala, 2008), despite some researchers contending that behavioral realism is more significant than form realism (Blascovich et al., 2002).
Increasing form realism could cause users to build social expectations for their interactions with avatars in the future (Nowak & Biocca, 2003) and design elements that are found to influence the degree of form realism of an avatar are:

- *Spatial dimensions*: avatars can be 2D or 3D, where compared to 2D equivalents, 3D avatars are thought to be more appealing and effective (Bailenson et al., 2008; Fox et al., 2015; Persky & Blascovich, 2007).

- *Movement*: increasing technological advances and client expectations have led to the development of visually more realistic and dynamic avatars capable of moving the body and face (Yun, Deng & Hiscock, 2009). Emotions can be conveyed via visually dynamic avatars with facial expression capabilities, which is very helpful for users from various cultural backgrounds: *"Avatars with high-intensity expressions and dynamics enable both local and global audiences to achieve approximately equal levels of subject identification and emotion perception"* (p. 21).

- *Human characteristics*: avatars can be given more human characteristics like name, gender, race, and age to increase the realism of the form.

According to Blascovich et al. (2002), the behavioral realism of avatars can help interactions with users feel more genuine. Design features that can be utilized to control the level of behavioral realism include:

- *Avatar interactivity*: the ability of avatars to interact bi-directionally is influenced by communication (the ability of avatars to communicate verbally, non-verbally, or by combining the two), the type of response (whether avatar answers are scripted or unscripted) and the presence of social content (whether or not avatars can converse about social and personal concerns, in addition to communications focused on tasks).

- *Control entities*: avatars can be controlled by an algorithm, a computer program, or by a human, the latter predictably increasing the behavioral realism of avatars as human-controlled avatars elicit greater social presence and influence than avatars controlled by computers (Fox et al., 2015).

Theoretically, an anthropomorphic look should improve customer outcomes, but practical research has revealed conflicting results. For example, in some studies, static, cartoony avatars with a very low level of form realism boosted customer satisfaction with a merchant, attitudes towards products, and purchase intentions (Etemad-Sajadi, 2014; Holzwarth, Janiszewski & Neumann, 2006). Nevertheless, Qiu and Benbasat (2009) discovered that more realistic human-looking avatars raised users' perceptions of social presence and raised usage intentions. According to Verhagen et al. (2014), there are no appreciable differences in service satisfaction between avatars with low and high formal realism.

Miao et al. (2022) attribute these inconsistent effects to the fact that these studies did not consider the sum of the parts that determine the realism of an avatar's form.

Similarly, several studies have highlighted the positive effects of behavioral realism, such as an increase in hedonic and utilitarian customer benefits during online purchases and related purchase intentions or a higher degree of trust generated in customers (Lee & Choi, 2017; Wang et al., 2007) but, nevertheless, there are also studies that lead to different conclusions.

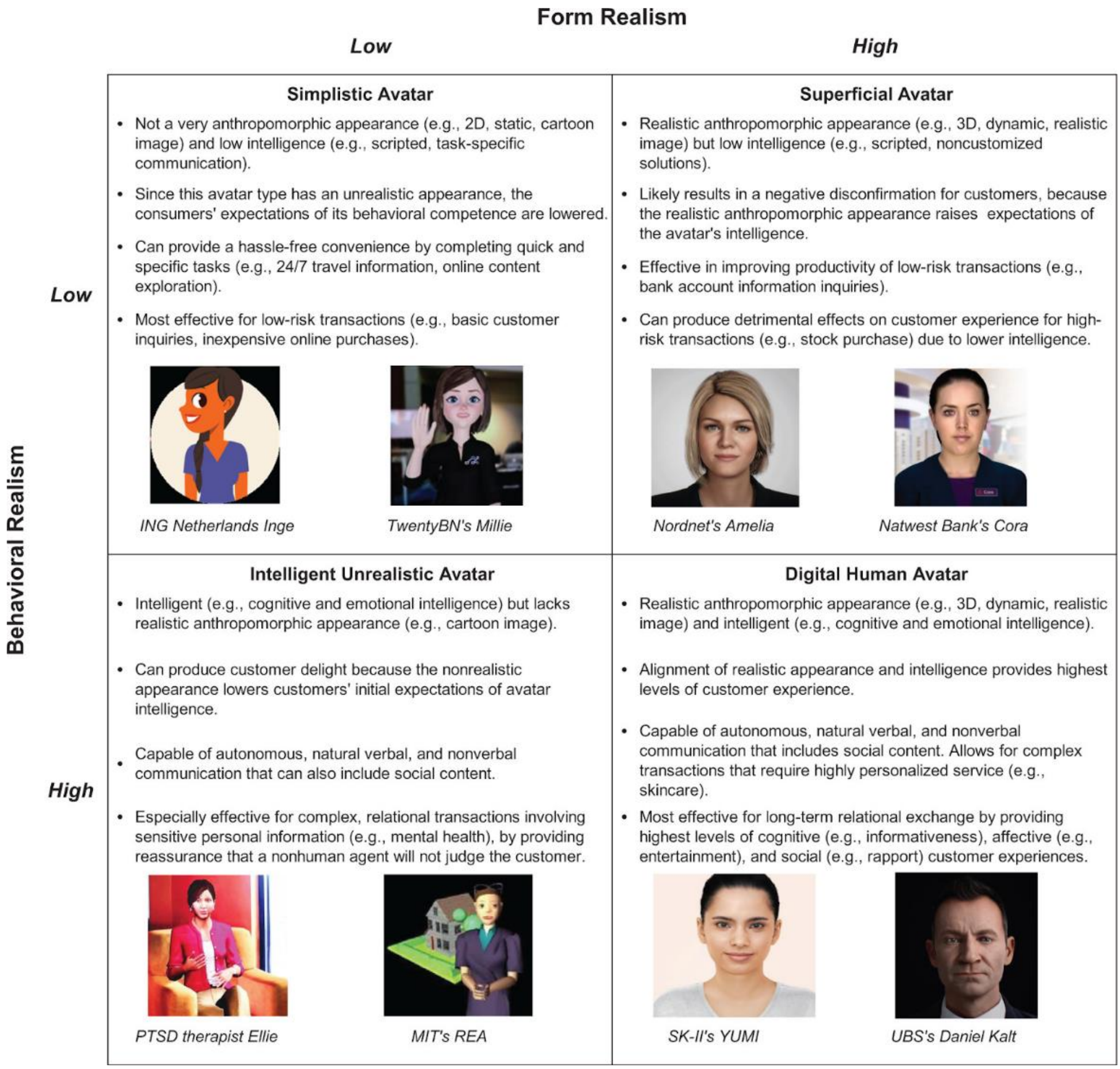
For instance, Bickmore, Pfeifer, and Jack (2009) discovered that a nurse avatar that included social content in its scripted conversations produced better patient experiences, but Schuetzler et al. (2018) discovered that a scripted, task-focused interviewer avatar elicits more socially biased responses.

According to Miao et al. (2022), the absence of concern for the alignment between avatar form and behavioral realism is a significant flaw in the existing literature on avatars. Because form realism only makes sense in the context of behavioral realism, form and behavior of avatars should be taken into account concurrently (Bailenson et al., 2008).

The usefulness of avatars can suffer significantly if the levels of form and behavioral realism are out of sync, which may help to explain why earlier results have been variable.

Based on form realism and behavioral realism, Miao et al. (2022) propose that avatars may be categorized in a 2 x 2 taxonomy way (Table III), which can be used to guide avatar design strategies and forecast whether or not avatars would be successful in business operations.

Table III - Form Realism versus Behavioral Realism (Miao et al., 2022)



Behavioral Realism	Form Realism: Low	Form Realism: High
Low	**Simplistic Avatar** • Not a very anthropomorphic appearance (e.g., 2D, static, cartoon image) and low intelligence (e.g., scripted, task-specific communication). • Since this avatar type has an unrealistic appearance, the consumers' expectations of its behavioral competence are lowered. • Can provide a hassle-free convenience by completing quick and specific tasks (e.g., 24/7 travel information, online content exploration). • Most effective for low-risk transactions (e.g., basic customer inquiries, inexpensive online purchases). *ING Netherlands Inge* *TwentyBN's Millie*	**Superficial Avatar** • Realistic anthropomorphic appearance (e.g., 3D, dynamic, realistic image) but low intelligence (e.g., scripted, noncustomized solutions). • Likely results in a negative disconfirmation for customers, because the realistic anthropomorphic appearance raises expectations of the avatar's intelligence. • Effective in improving productivity of low-risk transactions (e.g., bank account information inquiries). • Can produce detrimental effects on customer experience for high-risk transactions (e.g., stock purchase) due to lower intelligence. *Nordnet's Amelia* *Natwest Bank's Cora*
High	**Intelligent Unrealistic Avatar** • Intelligent (e.g., cognitive and emotional intelligence) but lacks realistic anthropomorphic appearance (e.g., cartoon image). • Can produce customer delight because the nonrealistic appearance lowers customers' initial expectations of avatar intelligence. • Capable of autonomous, natural verbal, and nonverbal communication that can also include social content. • Especially effective for complex, relational transactions involving sensitive personal information (e.g., mental health), by providing reassurance that a nonhuman agent will not judge the customer. *PTSD therapist Ellie* *MIT's REA*	**Digital Human Avatar** • Realistic anthropomorphic appearance (e.g., 3D, dynamic, realistic image) and intelligent (e.g., cognitive and emotional intelligence). • Alignment of realistic appearance and intelligence provides highest levels of customer experience. • Capable of autonomous, natural verbal, and nonverbal communication that includes social content. Allows for complex transactions that require highly personalized service (e.g., skincare). • Most effective for long-term relational exchange by providing highest levels of cognitive (e.g., informativeness), affective (e.g., entertainment), and social (e.g., rapport) customer experiences. *SK-II's YUMI* *UBS's Daniel Kalt*

Using this 2 x 2 taxonomy, the authors identified four distinct types of avatars:

- *Simplistic*: a simplistic avatar has minimal intellect (e.g., scripted, task-specific communication only) and an unrealistic human appearance (e.g., a 2D, visually static, cartoonish image). This kind of avatar would seem to be most useful for offering simple, hassle-free solutions for quickly doing specified duties (like selling high-quality products and answering inquiries), especially when the risk is low (as with affordable online shopping). One example is Millie, a sales cartoon avatar introduced by the start-up TwentyBN, who appears to be particularly successful in promoting inexpensive items such as eyeglasses and who can comprehend and respond to simple queries while presenting a variety of products (Kahn, 2018).

- *Superficial:* a superficial avatar has a realistic anthropomorphic look (e.g., 3D, visually dynamic, photorealistic image), but limited behavioral realism, in that it can only respond to queries with pre-programmed responses. Considering the lack of alignment between formal realism and behavioral realism, superficial avatars could amuse clients while boosting effectiveness in low-risk transactions (e.g., current account information), but, because these avatars lack the level of intellect that users might expect given their realistic anthropomorphic appearance, they may have unfavorable consequences for customers looking to engage in sophisticated or high-risk transactions (such as financial investments). Mixed results are seen when using superficial avatars in different industries. In line with what has just been said, Natwest Bank's Cora avatar in the United Kingdom is a very realistic-looking 3D avatar that can answer 200 basic questions, such as opening an account or filling out a mortgage application (Peddie, 2018), which is a very successful case while, on the other hand, the Swedish bank Nordnet was forced to stop using its realistic-looking avatar Amelia, presumably because of its inability to provide intelligent advice on buying stocks.

- *Intelligent Unrealistic Avatar*: an intelligent unrealistic avatar displays a non-realistic (for example, cartoonish) human appearance but possesses human-like cognitive and emotional intelligence. These very uncommon but typically successful avatars may interact with consumers in intricate real-time transactions without coming off as actual human salespeople. They appear to be especially useful for complex relational transactions involving private information (such as finances or health), as they can engender a feeling of non-judgment because users are aware that these avatars are not human, but are still proficient at their jobs. An example is the avatar therapist Ellie, used to detect symptoms of PTSD (Post Traumatic Stress Disorder) and depression in military veterans. According to Gonzalez (2017), these veterans reveal much more PTSD symptoms to Ellie than to a real-life therapist.

- *Digital Human Avatar*: a digital human avatar is the most sophisticated type of avatar, distinguished by an extremely realistic anthropomorphic form and human-like emotional and cognitive abilities, which is intended to deliver the maximum level of realism during interactions with human users. Digital human avatars seem to work best for creating lasting connections with clients in situations that involve a lot of complexity or risk (like financial investments), where clients value realism, dependability, and personalized service. One such is YUMI, an avatar created by SK-II that is remarkably lifelike in appearance and behavior and has advanced cognitive and emotional intelligence thanks to its artificial intelligence-powered digital brain. YUMI can understand users' movements and physical characteristics, such as eye color, interact verbally or via text, and offer trustworthy and highly individualized beauty recommendations (The Business Journals, 2019). Daniel Kalt from the investment bank UBS is another digital human avatar who can forecast financial data and give investment advice to very rich clients.

1.5 Relevance

1.5.1 Academic Relevance

Nicolas Pfeuffer et al. (2019) pointed out that anthropomorphic information systems, such as conversational agents, offer users a better experience and greater satisfaction with services if designed thoughtfully. In this sense, they believe there is a need to research the impact of anthropomorphic characteristics of information systems to assess their effects and create fresh design techniques that can be used as rules of thumb.

Among the anthropomorphic characteristics to which future research should pay particular attention is the sexual gender of AI, to investigate how gender biases are also effectively applied to artificial intelligence systems (Alabed, Javornik & Gregory-Smith, 2022; Diederich et al., 2022; West et al., 2019).

This phenomenon of study is especially relevant considering the current prevalence of AI agents with female characteristics (e.g., voice, name), which has also been alarmingly highlighted by UNESCO, for whom this prevalence risks reinforcing gender stereotypes (West et al., 2019).

In order to provide valuable insights for future research, Amani Alabed, Ana Javornik, and Diana Gregory-Smith (2022) compiled a preliminary research agenda for five different research directions and, in line with previous reports, they argued that future research should find answers to questions concerning the anthropomorphization of AI, such as: *"How might the gender aspects affect consumers' interactions with and perceptions of AI?* (Alabed, Javornik & Gregory-Smith, 2022, p. 15).

A recent study that investigated this phenomenon is attributed to Jungyong Ahn, Jungwon Kim, and Yongjun Sung (2022), who investigated the effects of gender stereotypes on the evaluation of AI recommendations for hedonic and utilitarian products. The authors found that the sexual gender of AI agents influences users' perceived levels of competence and warmth. Specifically, while warmth is valued more highly in the female AI agent condition than the male AI agent condition, male AI agents receive better competency scores than female AI agents. In addition to detecting this effect of AI gender on perceived levels of competence and warmth, this study found a significant interaction effect between the gender of AI and product type (utilitarian vs. hedonic), whereby consumers have a more positive attitude in conditions where the male AI recommends a utilitarian product, and the female AI recommends a hedonic product. Depending on the perceived personality (competent vs. warm), the effectiveness of recommendations made by AI agents changes: for utilitarian products participants trust the recommendations of male AI agents more than those of female AI agents and vice versa.

The results of this study offer some crucial managerial recommendations for businesses that are thinking about adopting AI agents but, as the authors also state, further research is needed to generalize these results, considering not only products but also places (Park, 2004) and services (Pizzi et al., 2021), which also fall under the categories of hedonistic and utilitarian sorts.

In fact, this thesis project aims to respond to the highlighted need to extend the study of gender prejudices' effects on AI recommendations to other contexts and subjects, and in fact, this study will consider not products, but rather hedonic and utilitarian services.

In addition, unlike the aforementioned study that investigated gender stereotypes' impact on poorly anthropomorphized chatbots, this research will consider a more advanced and highly anthropomorphized type of artificial intelligence, namely the Digital Human Avatar. This kind of artificial intelligence is characterized by a high degree of realism in form and behavior, which makes it ideal in contexts where customers require a personalized recommendation (Miao et al., 2022).

1.5.2 Managerial Relevance

Artificial intelligence is an important source of business value if well utilized, as automation offers the chance to cut expenses while giving corporate operations new levels of consistency, speed, and scalability.
As Accenture (2023) claims, thanks to the implementation of artificial intelligence, some of their clients are experiencing time savings of 70 percent and are recording three times the return on investment in this technology than those still stuck in the pilot phase.
Artificial intelligence, however, is not just about productivity and automating routine tasks; with the help of machine learning and deep learning, AI applications can also learn from data and outcomes in close to real-time, analyzing fresh information from numerous sources and adapting accordingly, with a level of accuracy that is extremely valuable to businesses (e.g., product recommendations). In this way, AI allows companies to adapt quickly, with a steady supply of insights to drive innovation and competitive advantage in a world that is constantly changing.
From this perspective, AI has the potential to be a major facilitator for a company's strategic priorities and even the pivot around which the very survival of the business revolves, so much so that "*three out of four top managers believe that by not scaling AI in the next five years, they will put their business at risk*" (Accenture, 2023). Some of the main benefits that artificial intelligence brings to businesses have been highlighted by Forbes (2023), and they are:

- *More accuracy and precision*: AI offers a high degree of accuracy and precision in its conclusion by decreasing human error. AI-based systems use a certain set of algorithms and historical data or information to make decisions. Errors cannot occur if artificial intelligence is correctly programmed.

- *No risk to human life*: by using AI robots to do their task, humans can simply avoid various risks that could have been faced by any individual. All hazardous jobs can be carried out with the assistance of an AI robot, without the direct involvement of humans. (e.g., exposing the ocean depths).

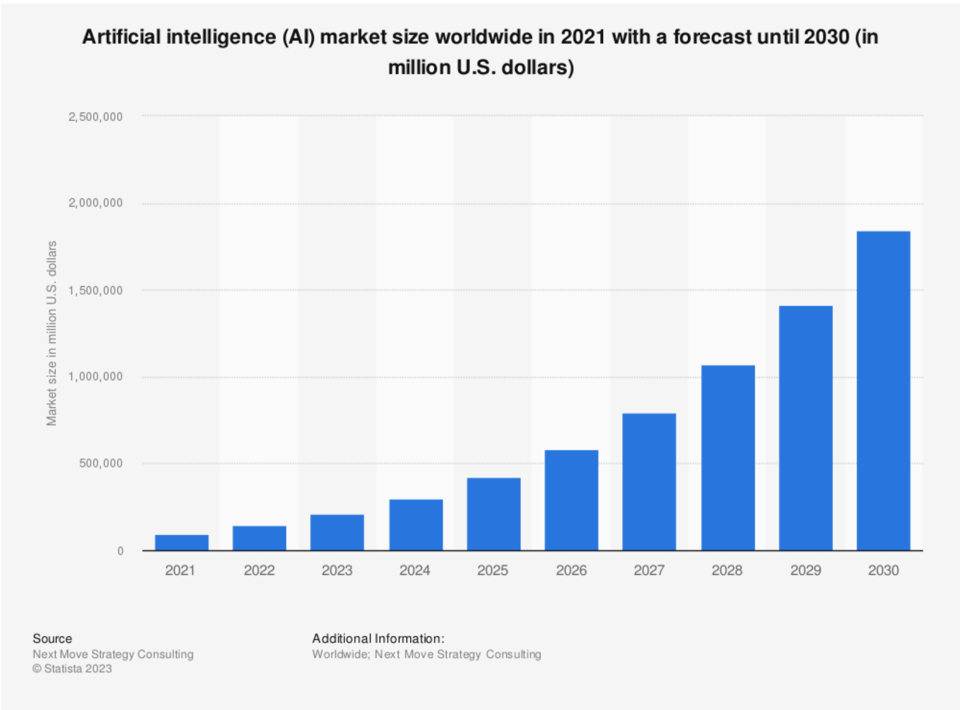
- *Available around the clock*: systems based on artificial intelligence can operate at any time of day. Artificial intelligence systems can operate continuously and complete more jobs with greater accuracy because they do not require any interruptions. Robots or artificial intelligence-based systems can even easily complete laborious and repetitive activities.

- *Serving customers digitally*: digital assistants powered by artificial intelligence are now being used by a number of cutting-edge businesses to deliver user-based content quickly. Now, businesses may build their own chatbots to assist them in quickly responding to all consumer inquiries.

- *Impartial approach*: artificial intelligence aids in making very realistic and logical decisions because it is not based on emotions and feelings. Artificial intelligence has the enormous benefit of being impartial, allowing for more precise decision-making.

In line with the great benefits that artificial intelligence makes available to businesses today, according to a McKinsey study on the state of Artificial Intelligence, from 2017 to 2022 AI adoption has more than doubled, as has investment in it. This growing investment in artificial intelligence by enterprises is consistent with the growing trend in the value of this booming market. According to Next Move Strategy Consulting, the artificial intelligence (AI) market was valued at $95.60 billion in 2021 and is expected to reach $1,874.58 billion by 2030, registering a CAGR of 32.9 percent from 2022 to 2030.

Figure III. Global artificial intelligence market size 2021-2030 (Statista, 2023)



The Marketing Science Institute (2020) has placed artificial intelligence as a priority in research for 2020-2022 because it is seen as an important technology that can significantly impact marketing management capabilities, strategies, function optimization, and accountability.

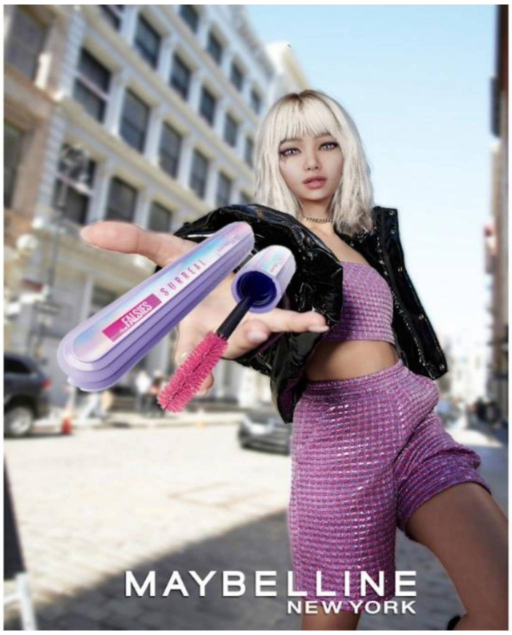
As also stated by Davenport et al. (2020), artificial intelligence (AI) is destined to have an impact on marketing tactics, as well as business structures, sales procedures, and customer service alternatives, along with consumer actions.

Under the business model currently used by online retailers, namely the shopping-then-shipping model, customers place orders and then the online retailer ships the ordered products to the recipients (Gans et al., 2017; Agrawal et al., 2018). However, with artificial intelligence, online retailers have the ability to predict what customers will buy, and assuming these predictions are highly accurate, they may switch from the present business model of shopping-then-shipping to one of shipping-then-shopping. Retailers will employ artificial intelligence to determine customer preferences as they transition to a shipping-then-shopping business model, providing things to customers without a formal order and giving them the option to return items they do not need (Gans et al., 2017; Agrawal et al., 2018).

Several companies now use artificial intelligence to try to predict what customers want, and they are experiencing varying levels of success (Davenport et al., 2020). As an example, Stitch Fix is an online personal styling service that recommends garments, shoes, or accessories to customers through cooperation between artificial intelligence algorithms and human stylists. Based on customers' responses to the digital survey on the website, algorithms, and stylists work together to predict which products customers want so that they can later send them five custom clothing and accessory items that perfectly match their style, size, and price preferences. Customers are free to keep the items chosen, especially for them, or send them back for free (Forbes, 2021). According to a McKinsey & Co. study of more than 400 AI use cases in 19 industries and 9 business functions, marketing and sales domains hold the greatest potential value for artificial intelligence (Chui et al. 2018). This is because these domains have an impact on marketing activities like next-best offers to customers (Davenport et al. 2011), predictive lead scoring (Harding 2017), and programmatic digital ad buying (Parekh, 2018). The most significant effects of AI on marketing are expected in particular in sectors like consumer packaged goods, banking, retail, and travel, i.e., sectors that naturally involve frequent interactions with large numbers of clients and produce huge volumes of data on transactions and customer attributes that can be used to offer tailored recommendations in real-time (Mehta et al., 2018).

According to Columbus (2019), marketers intend to leverage AI in areas including segmentation and analytics (in relation to marketing strategy) as well as messaging, personalization, and predictive behaviors (in relation to consumer behaviors). Artificial intelligence, therefore, enables companies working in digital marketing to inform consumers about the goods and services they offer and navigate more efficiently and effectively between choices. In addition, AI gives companies the chance to comprehend how clients interact with and perceive their solutions (De Bruyn et al., 2020), thus helping suppliers improve future offerings. According to Hanssens and Paschen et al. (2020), the use of AI in marketing is relevant in both B2B and B2C industries. In both situations, marketers can utilize artificial intelligence to better predict consumer needs, wants, and preferences and hyper-personalize value offerings to the extent that data and its analysis provide insights into customer preferences, perceptions, and actions. This could decrease customer turnover or cart abandonment and boost margin-enhancing outcomes like customer loyalty or good word-of-mouth (Libai et al., 2020; Cui et al., 2021; van Esch et al., 2021). Despite the great potential of AI, consumers still have reservations about it, which is a potential barrier to its adoption (DataRobot, 2022). According to research (Castelo et al., 2018; Gray, 2017), customers are less likely to employ AI for jobs involving subjectivity, intuition, and affect because they believe it lacks affectivity or empathy (Luo et al., 2019) needed to perform such tasks and relatively less able to identify the particularities of each customer (Longoni et al., 2019). Among the methods used to stimulate customer empathy toward AI is anthropomorphization, and a confirmation of this is the increasing use of avatars in contemporary marketing strategies. The use of avatars is anticipated to rise by 187 percent for consumer products and 241 percent for the travel and hospitality sectors, as businesses spend extensively on them to better interact with and serve their customers (Sweezey, 2019). According to Torresin (2019), 87 percent of banking organizations either already employ avatars or have plans to do so within the next two years. In the case of digital human avatars, which this study focuses on, the estimated value of the global market in 2020 was $10.03 billion and this value is expected to reach $527.58 billion in 2030 (Emergen Research, 2023). Digital human avatars are created based on a set of specific requirements that meet the user's needs, goals, and objectives, and their adoption as brand ambassadors of companies is currently growing. One example is May (Fig. IV), Maybelline New York's avatar featured in a spot in February 2023 on YouTube for the launch of the new *"falsies surreal extensions mascara"* (Inside Marketing, 2023).

Fig. IV - The avatar May by Maybelline New York



Other examples of this trend of using digital human avatars to promote products are Lil Miquela, a digital human avatar with more than 3 million followers on Instagram who has collaborated with brands such as Balenciaga, Channel, Coach, and Prada (Klein, 2020; Arsenyan & Mirowska, 2021), and Ling, a Chinese digital human avatar who has sponsored several famous brands, such as Bulgari, Estee Lauder, and Tesla (Andy & Tian, 2021). Digital human avatars have become especially popular since the introduction of the Metaverse, or the new 3D digital environment that allows users to enjoy authentic online personal and professional experiences through the use of virtual reality, augmented reality, and other cutting-edge Internet and semiconductor technologies (McKinsey, 2022). Since Facebook creator Mark Zuckerberg hired 10,000 people in Europe in 2021 to create his metaverse (IlSole24Ore, 2021), Internet searches for the term "metaverse" have increased by 7,200 percent (McKinsey, 2022). The interest in the metaverse is not only from consumers and, as a matter of fact, private capital is betting heavily on it: more than $120 billion flowed from the metaverse in 2022, and McKinsey (2022) estimates that by 2030, the metaverse might provide up to $5 trillion in value. By 2026, 25 percent of individuals will spend at least one hour per day engaging in activities such as work, study, socializing, entertainment, and/or shopping in the metaverse, predicts Gartner, Inc. (2022). This virtual world is set to impact every business that interacts with consumers daily, and for that reason, forecasts estimate that 30 percent of organizations worldwide will have metaverse-ready products and services by 2026 (Gartner, 2022). The metaverse has the power to reinvent brand-customer dynamics, create new touch points with customers, and constitute a new channel of engagement for employees and internal stakeholders as well, by grafting the experience into the corporate world at its different stages (PwC, 2023). One of the first brands that decided to invest in this new environment is Nike, the world leader in sportswear, which built on the Roblox game platform its imaginary city: Nikeland (Fig. VII) (Forbes, 2021). Nikeland, where all participating avatars wear Nike-branded products, represents for this brand a laboratory where it can analyze users' interests and, in fact, through this virtual world, the company aims to launch shoe prototypes for users to try on before starting mass production in the real world. In light of what has been reported in this section regarding the managerial relevance of this thesis project, it is important to keep in mind that although anthropomorphization allows consumers' skepticism toward artificial intelligence to be partly contained (e.g., Holzwarth, Janiszewski & Neumann, 2006; Etemad-Sajadi, 2014; De Visser et al., 2016; Chang et al., 2017; Seeger & Heinzl, 2018), of which digital human avatars represent a highly advanced form, companies need to pay attention to the effect that the human characteristics attributed to these digital entities have on perceptions of AI skills in relation to their type of business so that they can better match them to customer expectations and increase customer satisfaction. Specifically, the aim of this study is to investigate the existence of a gender bias against digital human avatars, whereby one gender is perceived as more skilled than another based on the service type (utilitarian vs. hedonic). Identifying this bias would prove to be of utmost relevance for all service providers who intend to use highly anthropomorphized forms of artificial intelligence to promote their services through personalized recommendations, especially in view of the great impact that virtual worlds such as the metaverse, of which avatars are an indispensable part, will have for businesses in the coming years.

2. Theoretical Framework

A theoretical summary of the current work will be given in this chapter. The primary study variables—Service Type, Expertise, Disclosure Willingness, and Avatar Gender—as well as their interactions, will be covered to establish the research hypotheses that will be investigated later in the thesis.

2.1 Service Type

Identifying an industry-wide definition of service is very difficult as services can be very different (Balin & Giard, 2006).
However, one of the most widely used definitions of services was developed by Kotler in 1987 and taken up in the various editions of his famous book *"Marketing Management: Analysis, Planning, and Control".*
Quoting Kotler's words in the fourteenth edition of the book 'Marketing Management' (2012), "A *service is any act or performance that one party can offer to another, which is essentially intangible and does not result in the ownership of anything*" (p. 356).
The concept of "intangibility" in Kotler's definition is due to William J. Regan, who coined the term IHIP in 1963 as an abbreviation of the four key traits that set services apart from goods: intangibility, heterogeneity, inseparability, and perishability.
Since Regan neglected to provide a detailed description of what these concepts mean, we can draw on the explanations offered by two university professors Stephen L. Vargo and Robert F. Lusch (2004):

- *Intangibility*: lacking the touch or perceptible aspect of good
- *Heterogeneity*: the difficulty in standardizing service production in comparison to that of goods
- *Inseparability of production and consumption*: the concurrent nature of service production and consumption as opposed to the physical items' sequential process of production, purchase, and use.
- *Perishability*: the difficulty of inventorying services in comparison to items

In light of the intangibility that distinguishes services from goods, services are usually more difficult to evaluate (Zeithaml, 1981) and, consequently, consumers experience a higher perception of risk with their purchase compared to goods (Zeithaml, 1981; Murray & Schlacter, 1990; Bateson, 1992).
Another system used to classify consumer services and goods is the SEC (Search, Experience, Credence) paradigm, which consists of three categories - search goods, experience goods, and credence goods (Nelson, 1970; Darby & Kami, 1973; Nelson, 1974).
He coined the term *"search qualities*" to describe the qualities of a brand that consumers can determine by inspection prior to purchase and "experience qualities" to describe those that are not determined prior to purchase, based on the assumption that customers are aware that the purpose of advertising is to persuade, including through exaggerations regarding product characteristics. Nelson coined the term "*search quality"* to describe the qualities of a brand that "*the consumer can determine by inspection before purchase*" and "*experience quality*" to refer to those that "*are not determined before purchase*" (Nelson, 1974, p. 730).

Darby and Karni (1974) popularized the concept that some qualities can never be verified by the typical consumer (for instance, when the consumer may not have the necessary technical expertise to evaluate the actual performance of the product). They also coined the term "*credibility qualities*" to describe qualities that, while valuable, cannot be evaluated in everyday use because more extensive and expensive research is needed. An example provided by the two authors could be "*the claimed advantages of the removal of an appendix, which will be correct or not according to whether the organ is diseased. The purchaser will have no different experience after the operation whether or not the organ was diseased"* (p.69).
Thus, considering the qualities that goods have, they can be classified as follows:

- ***Search goods***: goods whose attributes can be assessed before purchase or consumption.
- ***Experience goods***: goods whose attributes can only be evaluated after the product has been purchased or consumed.
- ***Credence goods***: goods whose attributes are difficult or impossible to evaluate even after consumption.

The simultaneous production and consumption of services is emphasized in many of the top textbooks in the field of marketing and management of services (Gronroos, 1990; Lovelock, 1991; Bateson, 1992; Palmer & Cole, 1995). The latter emphasizes how critical consumer and service provider relationships are on a personal level (Solomon et al., 1985). Other researchers have looked further into this interpersonal aspect of services, examining the value of relational components in relation to the "core" of the service in consumer evaluation (Crosby & Stephens, 1987; Iacobucci & Ostrom, 1993; Price et al., 1995), as well as the degree to which a service should be personalized (vs. standardized) (Blois, 1983; Surprenant & Solomon, 1987; Langeard & Eiglier, 1983). In light of the substantial diversity that exists within the service domain, Voss et al. (2016) make an argument for the significance of identifying the primary context within which firms operate and engage with their customers. Very useful in this regard is Higgins' (1998) Normative Orientation Theory, which is traditionally invoked to describe and distinguish between hedonic and utilitarian products.
Despite the fact that consumption entails both hedonistic and practical concerns, consumers generally tend to regard what they consume as predominantly hedonic or utilitarian (Khan, Dhar & Wertenbroch, 2005). Hedonic consumption is predominantly affective, based on sensory enjoyment, and it is measured by how satisfying a product is on an individual basis. Contrarily, utilitarian consumption is more cognitive, centered on functional objectives, and measured by how much a product serves as a tool to achieve a goal (Crowley, Spangenberg & Hughes, 1992; Holbrook, 1994; Botti & McGill, 2011).
While utilitarian consumption concentrates on functional outcomes, hedonic consumption highlights the sensorial, magical, and emotional aspects of the consumer experience.
According to Andréu, Casado-Daz, and Mattila (2015), hedonic services give customers hedonic values like thrill and enjoyment, whereas utilitarian services offer customers functional utilities or offer solutions to real-world issues.

When evaluating utilitarian services, customers are more practical and interested in problem-solving whereas, in hedonic services, customers are more interested in the service delivery, pleasure, and multi-sensual enjoyment evoked, captured with their experiential and affective benefits. In other words, in receiving a utilitarian service, customers are more interested in outcomes than in processes whereas, in the case of hedonic services, customers are simultaneously interested in consumption processes and outcomes (Lien & Kao, 2008). In light of the differences between hedonic and utilitarian consumption, it is not surprising that as the type of consumption (hedonic/utilitarian) changes, consumers' emotions and preferences vary.

The different emotional involvement between hedonic and utilitarian services has also been highlighted by Hellén and Sääksjärvi (2011), who took up a study conducted by Hightower, Brady, and Baker (2002) on the role that the physical surroundings play in the consumption of sporting events, which shows that customers expect hedonic services to be affective and encompassing, thus leading customers to perceive involvement as an important aspect when evaluating the quality of a hedonic service.

In contrast, for utilitarian services, happiness can be expected to have a direct connection with service quality as customers do not expect affective pleasure from utilitarian services and, therefore, they are unlikely to be involved in them.

Regarding the differences that exist between hedonic and utilitarian services, some studies have investigated the influence that the type of service has on the effectiveness of the different marketing appeals used to promote them. As an example, research conducted by Zhang et al. (2014) showed that purchase preferences for an experienced service (hedonic service) increase when an ad contains emotional elements, whereas purchase preferences for a belief service (utilitarian service) increase when an ad contains a rational appeal.

In light of the differences between hedonic and utilitarian consumption, it is not surprising that as the type of consumption (hedonic/utilitarian) varies, so do consumers' emotions and preferences.

Regarding the differences between hedonic and utilitarian services, some studies have analyzed the influence that the type of service has on the effectiveness of the different marketing appeals used to promote it.

According to research done by Zhang et al. (2014), purchase preferences for belief services (utilitarian services) increase when an advertisement makes a rational appeal, but purchase preferences for experience services (hedonic services) increase when an advertisement has emotional aspects. Another study related to the same area of research was conducted by Stafford, Stafford M. R., and Day (2002) on how the effectiveness of the type of spokesperson (service employee, celebrity, customer, and spokesperson character) used in marketing communications varies according to the type of service (utilitarian and hedonic) being promoted.

According to this study, a fictional character works well with hedonic services but not with utilitarian ones. A well-performing spokesperson for both categories of service is a celebrity, but the effects vary depending on the type of service. Specifically, scholars claim that the effectiveness of a celebrity testimonial in relation to a utilitarian or hedonic service varies according to the consumers' hedonic or utilitarian perceptions of the source of the promotional message, for which *"a celebrity such as Harrison Ford is likely linked to hedonic*

activities such as moviegoing, whereas a celebrity such as Bob Vila might be linked to more utilitarian activities such as fixing houses" (p.31).
Another related area of study worthy of consideration investigates the influence that individual consumer characteristics have on the perceived quality and fulfillment of hedonic and utilitarian services. Understanding long-term personality qualities is crucial from the perspective of services because they help identify clients who are more likely to have good service evaluations. Long-term personality traits also predict short-term emotional states.
For this reason, Hellén and Sääksjärvi (2011) investigated the impact that happiness has on service evaluation and engagement, as it is generally acknowledged that happiness has the power to influence life events positively or negatively, both large and small (Lyubomirsky, 2001).
Through three studies, the researchers found that:

- happier consumers evaluate the quality of utilitarian services more favorably than those who are less satisfied.
- happier customers are more engaged in hedonic services and as a result rate the quality of the service higher than those who are less satisfied (engagement works as a precursor to satisfaction with hedonic services).
- happier clients are more inclined to engage in hedonic services.

Given that people are predisposed to rate service quality in line with their level of happiness for both utilitarian and hedonic services, these results support the idea that service quality and engagement are somewhat driven by the personality of the client. In line with the study just reported, Jiang and Wang (2006) investigated the influence that affect has on perceptions of hedonic and utilitarian service quality.
Starting from the now common view that affect is an important aspect of consumption and influences quality assessment and satisfaction (e.g., Westbrook, 1987; Westbrook and Oliver, 1991; Mano and Oliver, 1993; Erevelles, 1998; Bagozzi et al., 1999), the two writers discovered a moderating relationship between affect (pleasure and arousal) and perceived service quality/satisfaction depending on the type of service (hedonic vs. utilitarian). Specifically, the results of the study show that pleasure and arousal have a greater influence on perceived service quality and satisfaction in the hedonic service context than in the utilitarian service context.

2.2 Disclosure Willingness

Given the growing importance of personal data in many industries, including marketing, the desire or reluctance to divulge personal information is a topic that has been extensively explored. In recent decades, predictive marketing based on customer personal data analytics has spread throughout numerous businesses and organizations worldwide (Artun & Levin, 2015). A growing number of businesses, both online and off, are attempting to gather personal information from their customers or visitors to use it for various analytical and/or communication objectives (Schofield & Joinson, 2008).

AI may help users with a variety of tasks (such as online shopping, information access, entertainment, and management of smart home devices) and provides several advantages to its users, such as enjoyment, utility, convenience, or personalization. Anyhow, to provide these functionalities and, specifically, to tailor the interaction experience to the user and their unique needs, AI must collect personal information. This suggests that AI gathers a lot of user data, which is problematic because both users and non-users of AI express worries about privacy and the volume of data that AI gathers (e.g., Azzopardi et al., 2018; Liao et al., 2019). Due to the significance of information privacy in the online buying process (Coşar, 2017), it has become an increasingly significant subject for academic research (Rohunen et al., 2018).

Understanding the elements that influence how people disclose their use of technologies is crucial in this situation. To date, research has examined associations between disclosure and individual user characteristics (e.g., Bansal & Gefen., 2010; Mohamed & Ahmad, 2012), trust in the technology provider (e.g., Joinson et al., 2010; Pal et al., 2020), as well as objective system traits (e.g., Easwara Moorthy & Vu, 2015) such as anthropomorphic design features (e.g., Lucas et al., 2014; Ha et al., 2021) and competence (Gieselmann & Sassenberg, 2022).

Self-disclosure (Collins & Miller, 1994) has been defined as "*any information about oneself that a person verbally communicates to another person*" (Cozby, 1973; Wheeless, 1976). This covers both categorical information (like one's political beliefs) and evaluative information (like one's feelings toward something).

The characteristics of depth (quality) and breadth (quantity) are commonly used to evaluate various levels of self-disclosure, as Collins and Miller have noted. According to Altman and Taylor (1973), width is the quantity of information shared, whereas depth is the degree of intimacy of the revelation.

Studies on disclosure behavior have investigated this object of research mainly from two different perspectives: some studies have regarded this behavior as one-dimensional while others have investigated it as multidimensional behavior.

The multidimensionality of disclosure behavior relates to the fact that the willingness to disclose information is not to be regarded as a general tendency whereby people who are inclined to disclose certain information have no problem with disclosing any kind of information: when asking for ten pieces of personal information, there will be people who have no problem with disclosing all ten items, people who disclose none and people who will only disclose some (Knijnenburg, Kobsa & Jin, 2013).

The motivations behind the behavior of disclosing personal information have been investigated from different theoretical perspectives. According to Social Exchange Theory (Thibaut & Kelley, 1959; Homans, 1961; Emerson, 1976), people consider the interpersonal costs and rewards of a social action before deciding whether or not to engage in it. Picking up on this concept, Laufer and Wolfe (1977) argue that enhancing the benefits associated with sharing personal information through the provision of benefits would provide financial relief from the act's expenses, which would result in consumers giving up more privacy. In line with this perspective, Resource Exchange Theory argues that, during marketing transactions, people trade their personal data for other resources and advantages. (Foa, 1971; Hirschman, 1980; Brinberg & Wood, 1983). As also suggested by the Expectancy Theory, people value benefits when calculating valences that directly influence their intention to seek privacy (Stone & Stone, 1990). Research that has identified the various motivational forces influencing consumer behavior includes economic analyses, which often assume that consumer choices are based on utilitarian criteria, such as financial gain or time savings. However, decisions are often dictated by needs that are not utilitarian, not such as self-fulfillment or social recognition (Howard & Sheth, 1969; Maslow, 1970; Hanna, 1980). The marketing literature suggests a synthesis of these many viewpoints by arguing that consumer behavior is driven by value, which is established by both utility and psychological need components (Babin et al., 1994; Dhar & Wertenbroch, 2000).

On the whole, advantages are categorized into those that provide intrinsic motivations and those that provide extrinsic motivations (Davis et al., 1992; Holbrook, 1999). People who are driven by extrinsic motivations behave to get advantages that help them reach other goals, whereas those who are driven by intrinsic motivations seek out the consumer experience as a means to an end.

A study on the factors influencing online disclosure (Hui, Tan & Goh, 2006) specifically identified seven categories of advantages that could persuade customers to give businesses their personal information.

Extrinsic benefits provide means by which consumers can fulfill other goals. Four important categories of extrinsic benefits are *monetary savings, time savings, self-enhancement,* and *social adaptation*:

- *Monetary saving* is one of the most common factors influencing consumer behavior and it includes rebates, coupons, presents, and loyalty points (Ailawadi et al., 2001; Chandon et al., 2000; Schindler, 1998; Sweeney & Soutar, 2001). Price turns out to be a component that significantly influences the choice of alternatives (Kamakura et al., 1996; McFadden, 1986, 2001) and in line with this assumption, Prospect Theory predicts that high financial gain can induce people to stop searching for alternatives and engage in choice (Kahneman & Tversky, 1979). In light of this, monetary savings directly influence consumers' willingness to engage in online transactions, despite the risks of privacy violations (Nowak & Phelps, 1997). People are willing to surrender their data in exchange for monetary compensation (Milne & Gordon, 1993) and some rank financial rewards above privacy security in evaluating websites (Hann et al., 2002).

- *Time saving* includes gains from improved convenience or effectiveness (Berkowitz et al., 1979; Berry, 1979; Bhatnagar et al., 2000; Darian 1987; Gillett, 1970). The assumption that consumers value time savings comes from home consumption economic theory (Becker, 1965, 1993; Lancaster, 1966; Ratchford, 2001). From this perspective, time is seen as an opportunity cost for consumers and is often considered along with price by consumers when assessing goods (Berkowitz et al., 1979).

- *Self-valorization* includes how people can enhance their perception of or regard for themselves in respect to others (Grubb & Grathwol, 1967; Shrauger & Schoeneman, 1979; Sirgy, 1982; Solomon, 1983). This concept is related to Impression Management Theory, which implies that people can confidently boost their self-concept by telling others what they are proud of so that others will feel the same way about them (Goffman, 1959; Leary & Kowalski, 1990; Tedeschi & Norman, 1985; Tetlock & Manstead, 1985). In line with the above, people keep their self-esteem strong by participating in activities that highlight their accomplishments or skills (Shavitt, 1990). From this perspective, it follows that instead of considering the utilitarian utility of a purchase, consumers could base their decision on symbolic aspects of self-improvement (Levy, 1959; Sirgy, 1982).

- *Social adaptation* refers to people's need to integrate with desirable social groupings in order to develop a social identity (Baumeister & Leary, 1995; Csikszentmihalyi & Rochberg-Halton, 1981; Maslow, 1970; Shavitt, 1990; Smith et al., 1956; Sweeney & Soutar, 2001). This concept is in line with Self-Categorization Theory, which argues that personal identity is lost in favor of depersonalization when one seeks to associate with desired groups (Turner, 1982; Turner et al., 1987; Turner & Onotaro, 1999). These theoretical reasons imply that it is possible to influence customer behavior by assisting them in adjusting to preferred social circumstances.

Intrinsic benefits are an end in themselves for customers. Three important categories of intrinsic benefits are *pleasure, novelty,* and *altruism:*

- *Pleasure* is a feeling of pleasure or enjoyment (Mehrabian & Russell, 1974) that results from certain products or services. The Inversion Theory holds that people oscillate between two arousal levels (Russell et al., 1989): people might prefer arousing activities (like playing video games) when they are depressed, and when they are aroused, they may favor soothing ones (like listening to music). Hedonic motivations are frequently linked to pleasure because people naturally crave enjoyment, leisure, fantasy, enthusiasm, and fun (Hirschman & Holbrook, 1982).

- *Novelty* includes the methods by which individuals can satiate their intrinsic desires for discovery or information (Baumgartner & Steenkamp, 1996; Kahn & Louie, 1990; Kahn & Raju, 1991). People may be inspired to learn more when they see data that shows how inadequate their knowledge is (Malone, 1981).

- *Altruism* manifests itself in acts that people perform only to improve the well-being of others, without selfish motives (Baumeister, 1982).

Table IV- Typology of Benefits (K.-L. Hui et al.)

Extrinsic Benefits	Intrinsic benefits
Monetary saving – reduce money spent, gain free gifts	**Pleasure** – gain pleasant experience, gain enjoyable experience
Time saving – reduce time spent, gain convenience or efficiency	**Novelty** – explore unfamiliar domains, fulfill information needs
Self-enhancement – assert self –concept, maintain self-esteem	**Altruism** – help others without motives, empathize with others
Social adjustment – gain social approval, adhere to social norm	

The Privacy Calculus Theory (Culnan & Armstrong, 1999), which examines the factors that encourage or dissuade customers to share information online, has typically served as the foundation for current research in this area. This idea holds that while selecting whether to release personal information, people must weigh the expected advantages against the risks of privacy loss (Robinson, 2017; Smith et al., 2011).

In exchange for a chunk of their privacy, people expect to get customized offers from released data (Montecchi & Plangger, 2020), in line with the previously mentioned Social Exchange Theory (Emerson, 1976; Homans, 1961; Thibaut & Kelley, 1959).

In line with this perspective, White (2004) conducted a study on consumers' motivations to disclose personal data to relationship-focused advertisers, specifically exploring the impact of customers' perception of relationships, the nature of the advantages offered by advertisers in return for the information asked and the kind of information requested.

The findings demonstrate that, depending on the type of information asked as well as the nature of the relationship between the consumer and the vendor, the willingness to divulge private data in exchange for a targeted marketing offer lowers.

Specifically, the results reveal that individuals who have a deep relationship with the seller are more likely to provide information related to their privacy (compared to those who do not have a deep relationship with the seller) but more reluctant to provide the information when it is 'embarrassing'.

Regarding an individual's perspective of what happens after the information is submitted (Dinev & Hart, 2006), privacy concerns are a prominent dispositional belief (Bansal et al., 2016). This concept refers to the *"degree to which an individual believes that a high potential for loss is associated with the release of personal information to a company"* (Xu et al., 2011, p. 13). Privacy concerns in online settings are a reflection of how much people fear losing anything by sharing personal information (Dinev & Hart, 2006).

A study conducted by Fernandes and Pereira (2021) on the motivations behind the disclosure of personal data online in transactional contexts (i.e., associated with commercial contexts including online banking, e-commerce, online travel websites, streaming services, and e-health services branded mobile apps) investigated the influence of habits, utilitarian benefits, hedonic benefits, and privacy concerns on this behavior.

The examination of the data revealed that habits, utilitarian benefits, concerns about privacy, and finally hedonic rewards were the most important determinants of data disclosure.
Thus, this study showed that although prior investigation has identified utilitarian benefits (e.g., utility and convenience) as the primary factor that consistently affects both the beginning and maintenance of a particular behavior (Limayem et al., 2007), self-disclosure appears to be mostly unconscious (Plangger & Montecchi, 2020) or automatic (Bol et al., 2018).
This is consistent with the Theory of Planned Behavior (Ajzen, 1985), according to which habitual attitudes and intentions are formed through repeated conduct and once activated, automatically direct behavior without the need for conscious mental effort (Verplanken & Wood, 2006). Prior habits are especially important in environments that are diverse and dynamic, such as the digital landscape, and people frequently use heuristics to speed up decision-making when they feel cognitively overloaded or are constrained by information asymmetries (Plangger & Montecchi, 2020; Kokolakis, 2017). Therefore, from a behavioral standpoint, consumers exploit cognitive biases to make up for their poor rationality when making judgments about data sharing (Acquisti & Grossklags, 2005, 2007; Gerber et al., 2018; Wakefield, 2013). Although this research highlighted the dominant role of irrationality in the decision-making process behind the willingness to disclose one's information online, it must be acknowledged that utilitarian benefits were found to be the second most significant factor in predicting disclosure, outweighing even privacy concerns. This result is in line with previous studies showing that if a consumer feels that providing personal information would be valuable and convenient, they are more likely to do so. (Krafft et al., 2017).
Considering the greater importance that utilitarian benefits show on the disclosure of personal information than hedonic benefits (Culman & Amstrong, 1999; Kraft et al., 2017; Robinson, 2017; Smith et al., 2011), it can be argued that customers will be more willing to provide their personal data for utilitarian rather than hedonic service recommendations.
Hence, the following hypothesis has been formulated:

H1: The Utilitarian service type has a more positive impact on the disclosure willingness compared to the hedonic one.

2.3 The Mediating Role of Expertise

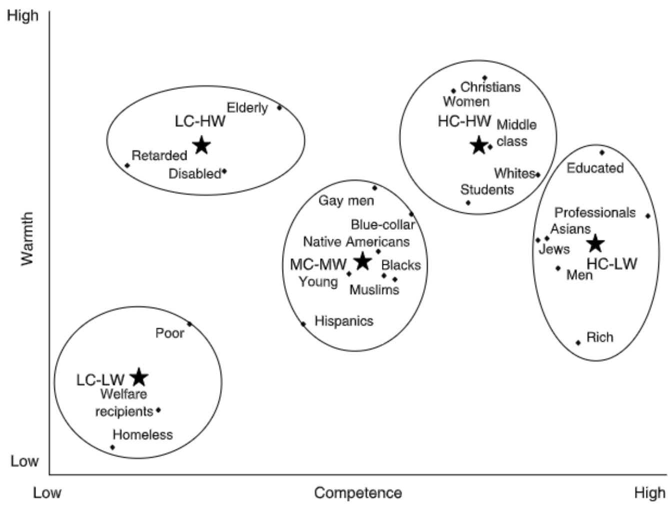
Hovland et al. (1953) identified "expertise" as *"the extent to which a communicator is perceived to be a source of valid assertions"* (p. 21).
Expertise, also known as "authoritativeness" (McCroskey, 1966), "competence" (Whitehead, 1968), "qualification" (Berlo, Lemert & Mertz, 1969), or "expertness" (Applbaum & Anatol, 1972), is the second aspect of source credibility (together with attractiveness). In accordance with the Traditional Source Credibility Model (Hovland, Janis, & Kelley, 1953; Hovland & Weiss, 1951; Johansson & Sparredal, 2002; Ohanian, 1990) and the Source Attractiveness Model (Johansson & Sparredal, 2002; McGuire, 1968, 1985),

qualities like expertise, trustworthiness, and attractiveness have been measured as positive features that significantly provoke receivers' positive attitude and even purchasing (Applbaum & Anatol, 1972; Hovland et al., 1953).

According to previous research on source expertise in persuasion (Horai, Naccari & Fatoullah, 1974; Maddux & Rogers, 1980; Mills & Harvey, 1972; Ross, 1973), the source's perceived expertise has a favorable effect on attitude change. In line with the latter statement, a higher subjective perception of competence seems to be associated with an increased trust in and positive attitude toward AI (Pitardi & Marriott, 2021).

Competence (ability and security), together with warmth (trustworthiness and friendliness), appears to be one of the primary dimensions of social perception according to the Stereotype Content Model (SCM) produced via studies on social cognition (Fig. V).

Fig. V - Group competence-warmth stereotypes (Fiske et al., 2002)



According to Cuddy, Fiske, and Glick's (2008) contention, the functional significance and universality of the warmth and competence dimensions result from their relationship to two key concerns for existing and flourishing in the social world.

Actors must first anticipate the intentions of others toward them; the warmth dimension, which comprises qualities like trustworthiness, morality, kindness, sincerity, and friendliness, evaluates how the other is regarded to be acting in a social setting.

Second, actors must be aware of other people's capacity to carry out their intentions in both a temporal and important manner. This is where the competence dimension comes into play, which is defined as the perceived capacity to carry out intentions and includes qualities like efficacy, creativity, skill, confidence, and intelligence.

Warmth, from the perspective of motivation, is an accommodating orientation that prioritizes others over self, whereas competence is the self-profitable characteristics associated with the capacity to bring about desired outcomes (Peeters, 1983).

In other words, according to assessed intentions and skills, actors distinguish between people and groups based on how they are likely to affect them or the ingroup (Cuddy, Fiske, & Glick, 2008).

In the case of spokespersons, celebrity endorsers, and salespeople utilized in advertising, marketing, retail, promotion, and e-commerce, both competence and warmth are highly significant personality attributes (Ahn, Sung & Kim, 2022).

These two qualities are relevant since they are both necessary for trust (Sung & Kim, 2010). The consumer's faith that the good or service will provide quality performance in a trustworthy, accountable, and competent manner is related to competence. It refers to the degree to which a brand is viewed as knowledgeable and competent as a result of experience or formal training in the product/service category. For instance, Casal et al. (2007) argued that competence is essential to e-commerce.

These two dimensions appear to be fundamental to the formation of the impression underlying human perception of other humans (Russell & Fiske, 2008) and non-human agents that seem to have an intention such as animals (Sevillano & Fiske, 2016), robots (Carpinella et al., 2017), and consumer brands (Kervyn, Fiske, & Malone, 2012). Regarding the final category, Khadpe et al. (2020) showed the applicability of these two dimensions for chatbots, suggesting that AI systems may place a premium on feelings of warmth and expertise.

Although variables such as warmth and competence appear to be very important for AI adoption, it is important to keep in mind the possible interference of individual consumer characteristics.

Individuals with anxious attachment desire intimacy in a social interaction, but at the same time are concerned about obtaining unreliable social feedback (Mikulincer et al., 2003; Gillath et al., 2005).

This means that, in contrast to people, objects (such as robots) are viewed as being incredibly trustworthy, especially when it comes to social feedback (Keefer et al., 2012). According to earlier research (Paiva et al., 2017; Wirtz et al., 2018), people perceive robots as being less socially expressive, less empathetic, and less capable of understanding human feelings. However, they are also thought to be less able to display social cues that could be interpreted as possible signs of depreciation. Such an aspect of the human-robot relationship may be attractive to people confronted with the possibility of receiving unreliable social feedback from others (Joireman et al., 2002).

In accordance with the foregoing, an interesting investigation by De Angelis et al. (2021) discovered that people who scored poorly (vs. well) on tests of anxious attachment style (AAS) had a more negative reaction to frontline support robots than people who scored highly (vs. a human frontline agent).

Similarly, Yuan, Zhang and Wang (2022) found that when users are socially anxious, the benefits of AI assistants (e.g., compatibility, responsiveness and anthropomorphism) lead to an increased perception of utilitarian/hedonic values and this positively impacts their experience and loyalty.

AI adoption also appears to be influenced by the perceived risk of the consequences that the tasks performed have on consumers' lives. Using AI for tasks with greater consequences is perceived as a higher risk (Bettman 1973), which in turn reduces adoption intentions (Castelo & Ward, 2016; Castelo et al., 2018).

Castelo and Ward (2016) contend that women are less likely to adopt AI than men are, particularly when the results are important since they perceive danger differently from males (Gustafsod, 1998) and take less risk (Byrnes et al., 1999).

The relevance of a task to a customer's identity would appear to be another aspect, in addition to demographics, that would seem to determine the amount of AI adoption.
Customers may be less inclined to adopt AI when a task is significant to their sense of self (Castelo, 2019), as they tend to want to claim ownership of the outcomes of their consumption when a task is important (Leung et al., 2018).
The use of AI for these consumption activities might be understood by customers as cheating, and this hampers credit allocation after consumption (Davenport et al., 2020).
Most recently, the adoption of artificial intelligence for product and service recommendations has steadily increased but the acceptance of recommendations by customers depends on several variables, including the accuracy of AI-generated information (Kim, Giroux & Lee, 2021) and the type of product/service recommended.
Task characteristics particularly influence the adoption of AI. Specifically, consumers are likely to feel less comfortable with AI when a task appears subjective and involves affect or intuition (Castelo, 2019).
Research confirms that consumers' lower propensity to use AI for subjective, intuitive, and affective tasks stems from the fact that AI is perceived as lacking the empathy or affective skills needed to perform such tasks (Castelo et al., 2018).
As pointed out by Longoni and Cian (2022), people believe that artificial intelligence advisors are more (less) competent in assessing the utilitarian (hedonic) value of attributes and generating utilitarian-oriented (hedonic) recommendations than human advisors. This is because humans and AI are seen to have varying degrees of skill in terms of analyzing information. Humans are thought to possess emotions and experiential skills, whilst AI, robots, and computers are thought to possess reason and logic. Thus, the preference of human (AI) over AI (human) recommendations in the case of hedonic (utilitarian) consumption depends on the fact that hedonic value assessment is based on experiential, emotional, and sensory criteria whereas utilitarian value assessment is based on factual, rational and logical evaluation criteria (Longoni & Cian, 2022).
The connection between perceived AI competence and utilitarian contexts is further supported by a study by Belanche, Casaló, Schepers, and Flavián (2021), who discovered that perceived robot competence primarily affects consumers' utilitarian expectations (i.e., functional and monetary value), whereas perceived warmth only affects their relational expectations (i.e., emotional value), particularly for those with a need for social interaction.
In line with what has just been reported, according to research done by Liu, Yi, and Wan (2022) on the impact of robot appearance and type of service on customers' and tourists' intentions to use robots in the hospitality industry, consumers are more willing to use a service robot viewed as warm in hedonic service contexts than they are to use one perceived as competent in utilitarian service contexts.
Drawing upon past research, it can therefore be said that consumers prefer to base their purchasing behavior on AI recommendations over human recommendations when consumption is predominantly utilitarian, whereas when consumption is predominantly hedonic, human recommendations are preferred over AI recommendations.

Formally:

H2: The perceived Avatar expertise mediates the relationship between the service type and the disclosure willingness. The Utilitarian service type (vs Hedonic service type) increases the perceived Avatar expertise by users.

The relevance of expertise for the adoption of AI can also be linked to the willingness of users to share their data, which is the basis for the efficient and personalized performance that artificial intelligence can offer us. This connection between expertise, also called competence (Whitehead, 1968), and the willingness to provide personal data was investigated by a study conducted in 2022 by Miriam Gieselmann and Kai Sassenberg. Through a distinction between intellectual competencies (e.g. anticipating and making plans, coming up with creative solutions, and handling difficult or insufficient information) and meta-cognitive heuristics (e.g. learning, developing, and adapting universal strategies based on previous events and interactions), these two authors found that users are open to sharing personal information in exchange for the intellectual capabilities of AI, and meta-cognitive heuristics only minimally enhance privacy issues while remaining unaffected by user openness to sharing information.

Another recent study on the connection between perceived competence and consumers' propensity to trust AI was conducted by Pizzi et al. (2023), who discovered that when a chatbot is perceived as competent, people are less skeptical about the technology—but only when they think they are capable of accurately discerning others' ultimate intentions.

Considering what was said above, the following hypothesis has been stated:

H3: The perceived Avatar expertise mediates the relationship between the service type and the disclosure willingness. A higher perceived Avatar expertise leads to a higher disclosure willingness.

2.4 The Moderating Role of Avatar Gender

Customers typically trust humans and avoid autonomous technology, according to Baccarella et al. (2021), since artificially intelligent systems are thought to be less capable of giving trustworthy, competent, and relevant information.

Customers in particular view automated systems as being less adaptable and flexible, particularly in conditions defined by significant uncertainty (Leo & Huh, 2020) or circumstances that call for an explanation, such as when a poor service outcome occurs (Huang & Qian, 2021).

In accordance with the foregoing, a study by De Angelis, Donato, Pozharliev, and Rossi (2022) discovered that in the event of a poor service outcome, customers are happier with the service provided by autonomous vehicles (AV) than by human agents because humans are viewed as more competent and, consequently, more responsible for service failure.

To reduce consumer resistance, artificial intelligence (AI) agents with anthropomorphic designs are becoming more and more common, with significant advances occurring particularly in the hospitality sector (Fan et al., 2020; Lu et al., 2019; Yu, 2020).

In fact, one of the main objectives of anthropomorphic design is to influence in a positive way the affections of human beings, which has been observed to be an important factor in human-robot interaction (HRI) and marketing (Eyssel et al., 2010; Qiu et al., 2020).

According to De Visser et al. (2017), designers think that highly anthropomorphic AI service agents can increase the willingness of users to employ them, hence boosting commercial success.

Qiu and Benbasat (2009) found that an anthropomorphic design, particularly anthropomorphized voices, and the embodiment of the product recommendation agent (PRA) positively influence social presence, which in turn increases the trust and credibility of the technology agent's suggestions.

Systems or robots that are embedded with anthropomorphic cues can have a variety of positive effects, including increased sympathy brought on by a social or emotional connection (Eyssel et al. 2010), better purchasing decisions brought on by more natural interaction (Qiu & Benbasat, 2009), or even improved sociability in children with autism spectrum disorders (Bernardini et al., 2014).

According to Aggarwal and McGill (2007), consumers will value and accept a product more the more it resembles a human being. AI service agents' anthropomorphic designs reflect the psychological propensity to give non-human objects human traits (Heider & Simmel, 1944). Accordingly, most AI service agents are created with human qualities, encompassing both psychological (language style, emotions, etc.) and non-psychological (appearance, gestures, etc.) characteristics.

Anthropomorphic characteristics, such as physical appearance (Eyssel & Hegel, 2012) and voice (Powers et al., 2005; Siegel et al., 2009), can also influence how the biological gender of an Information System (IS) is perceived, which in turn triggers behaviors, cultural norms, and psychological characteristics that are typically associated with men or women (Pfeuffer et al., 2019).

Sexual gender is a component of who we are that controls the kind of social behavior or acts we engage in *"by managing situated conduct in light of normative conceptions of attitudes and activities appropriate to one's gender category"* (West & Zimmerman, 1987, p. 127).

Gender, according to De Beauvoir (1973), is something we internalize over time through performative behaviors rather than something we are born with.

In this way, Judith Butler contends that gender has a performative quality since gender identity is the result of repeated, stylized actions that over time reveal a *"cultural interpretation or signification of that [biological] factuality"* (Butler, 1990, p. 522).

Due to this *"need to routinize (...) behavior following pre-established conceptualizations and behavioral patterns"* (Deaux & Major, 1987, p. 370), specific traits and behaviors are classified as feminine or masculine and are taken to indicate a person's preferences and actions (Costa, 2018).

According to Prentice and Carranza's argument, "prescriptive gender stereotypes" specify *"the qualities [attributed] to women and men (...) that are required of women and men"* (2002, p. 269).

In light of what has just been reported, it is possible to argue that gender stereotypes are both descriptive, in the sense that formed around a quality that a woman or man possesses, and also prescriptive, i.e., they depict what society believes a person should be based on their gender (Brahnam & De Angeli, 2012).

To put it another way, gender stereotypes affect how people view and interpret information about themselves, but they also affect how others perceive them (Ellemers, 2012).

Social Role Theory provides an explanation for stereotypes, which suggests that individuals, once they have formed strong beliefs about gender, associate these beliefs with specific social roles for men or women, i.e., behavioral expectations (Hentschel et al., 2019; Guo et al., 2020). Accordingly, gender stereotypes are irrational beliefs about a person's gender that suggest that women and men behave differently based on their gender (Brahnam & De Angeli, 2012). These stereotypes lead to inaccurate assessments that could have an impact on decisions or performance expectations (Hentschel et al., 2018; Hentschel et al., 2019).

Previous research on social categorization has demonstrated that people frequently categorize and generate impressions about others based on cues like a person's gender, age, or ethnicity (e.g., Bargh, 1999; Devine, 1989; Tajfel, Billig, Bundy & Flament, 1971).

Social categorization has several important repercussions (Bodenhausen, Kang, & Peery, 2012), including the activation of stereotypes and other group-related ideas and associations in memory that affect subsequent judgments. A person who is classified as female, for instance, will be viewed in a way that is compatible with gender stereotypes associated with women (e.g., friendly, kind).

In addition to beliefs and associations, social categorization also activates the evaluations connected to the category, i.e., attitudes (Stroessner & Benitez, 2019).

The cognitive processes of social categorization and the resulting social evaluations that underlie people's perceptions also appear to have a major role in the perception of robots and other non-human entities (Epley, Waytz, & Cacioppo, 2007).

Several studies have tried to confirm the assumption that the stereotypes underlying human perception are also projected onto non-human agents. According to a study by Nass, Moon, and Green from 1997, the gender stereotypes that people hold about men and women can be triggered by the voice that a computer reproduces. Male voices make a computer sound more convincing than when the same praise is delivered by a female voice.

Similarly, a study by Ernst and Herm-Stapelberg (2020) found that people perceive virtual assistants (e.g., Siri) with a male voice as more competent than those with a female voice.

Eyssel and Hegel (2012) showed in their study that the sexual gender of robots, made explicit by aesthetic clues such as haircuts, activates gender stereotypes that influence the type of tasks (male vs. female) perceived as more suitable for robots (male vs. female).

Powers and colleagues (Powers & Kiesler, 2006; Powers et al., 2005) showed that a robot's behavior, appearance, or tone of voice constitute important hints for subsequent robot judgments, suggesting that individuals *"do not approach the robot tabula rasa, but rather develop a predefined model of robot knowledge"* (Powers et al., 2005, p. 159).

Shifting the focus from robots to chatbots, Fox and Nowak (2018) argue that when anthropomorphic chatbots (e.g., avatars) present a certain sexual gender, gender stereotypes are activated that lead people to expect them to have gendered knowledge, influenced by the general stereotyping of men and women.

The Computers Are Social Actors (CASA) framework, which contends that people respond to media agents without thinking and interact with them using the same script for interactions between human beings, can help to explain this attribution of (gender) knowledge and stereotypes to chatbots (Nass & Moon, 2000). People tend to expect women's qualities to be related to commonality; they should be helpful, warm, and caring, while men's stereotypical dominance refers to their competence, agency, and authority (Ellemers, 2018). Theoretically, these stereotyped responses and expectations may be applied to chatbots as social agents, as proposed by Bastiansen, Kroon, and Araujo (2022).

Similar to human-human scripts, these human-machine scripts can be used subconsciously (Gambino et al., 2020).

According to several studies, stereotyping is more likely to happen when technology is applied in areas that are specific to either gender rather than in areas that are gender-neutral. As a result, when a woman is represented by technology, people judge her to be more competent in fields that are more common for women than in technical or other fields that are seen to be more male-centric, and the opposite is also true. Therefore, when a task is performed by technology that is gender-neutral, gender stereotyping is less likely to happen. This finding suggests that people do not intentionally discriminate against technology, but rather unconsciously use stereotypes in the virtual world (McDonnell & Baxter, 2019; Dufour, Ehrwein & Nihan, 2016).

In this regard, UNESCO has recently drawn attention to the prevalence of female-sexualized digital assistants, particularly in the case of conversational voice assistants (CVAs), which are mainly comprised of young, submissive women. Examples of such CVAs include Amazon's Alexa, Microsoft's Cortana, Apple's Siri, and Google's Assistant. UNESCO claims that these design decisions can serve to promote gender stereotypes (West et al., 2019).

Companies and developers justify the design decisions by referencing market research that demonstrates how male and female voices are seen differently in terms of trustworthiness and collaboration (Schwär & Moynihan, 2020; Schild et al., 2020). Because of this, women are frequently given the job of personal assistants, while businesses typically select male voices for conversational voice assistants (CVA) in situations when the CVA needs to be authoritative.

The knowledge we have regarding the implications of the sexual gender attributed to artificial intelligence is still insufficient and several scholars argue that it is a phenomenon that needs to be studied in greater depth, especially in light of its increasing adoption.

Nicolas Pfeuffer et al. (2019) argue that future research should pay particular attention to the effects that anthropomorphic features of AI have on the trust and acceptance of information system users. Similarly, Amani Alabed, Ana Javornik, and Diana Gregory-Smith (2022) argue the importance of studying the effect that gender bias has on AI perception and adoption.

One study that set out to investigate the influence of gender on perceptions of AI was published by Jungyong Ahn, Jungwon Kim, and Yongjun Sung in March 2022. This work studied the effect of AI gender (independent variable) on the perceived warmth and competence of the AI, which is hypothesized to have an influence (through mediation) on the persuasive effect of AI recommendations. According to the conceptual model devised by these scholars, the type of product (utilitarian vs. hedonic) moderates the relationship between perceived AI competence/warmth and the persuasive effect of AI recommendations.

The limitations of this study include the fact that it only considered the world of products and not the world of services, on which this study will focus instead.

Moreover, the previously mentioned study focused specifically on chatbots, whereas this research instead has as its object of study a type of highly anthropomorphized artificial intelligence, the Digital Human Avatar, which, compared to other types, is characterized by a high degree of realism in form and behavior, making this type of avatar ideal when customers require a highly personalized service (Miao et al., 2022).

Therefore, the present research aims to investigate the influence that the sexual gender of artificial intelligence has on the expertise perceived by users in relation to the type of service (hedonic vs. utilitarian) that is recommended. In light of what has been reported, it is expected that female (vs. male) AI is perceived as more competent when the recommendation is related to a hedonic (vs. utilitarian) service and vice versa.

Putting this formally:

H4: The Avatar Gender moderates the relationship between service type and perceived Avatar expertise. In particular, the female gender related to a hedonic service leads to a higher perceived Avatar expertise, whereas the male gender related to a utilitarian service leads to a higher perceived Avatar expertise.

2.5 Conceptual model

The various research reported in this chapter contributes to laying the foundations for the four hypotheses that constitute the conceptual model that this research seeks to confirm.

The Privacy Calculus Theory (Culnan & Armstrong, 1999) and the studies on the motivations behind the disclosure of personal information mentioned above argue that when consumers have to decide whether or not to disclose their data, they evaluate and compare the expected benefits and costs of the loss of privacy (Robinson, 2017; Smith et al., 2011) to make the most useful and convenient decision for them (Krafft et al., 2017).

Deciding whether or not to disclose one's data based on evaluations of the expected costs and benefits of loss of privacy appears to be more consistent with a utilitarian rather than a hedonic type of service, as the evaluation of utilitarian services involves fundamentally practical reasoning, whereas the evaluation of hedonic services involves abstract reasoning (Botti & McGill, 2011; Crowley, Spangenberg & Hughes, 1991; Holbrook, 1994).

Considering the above, the first hypothesis (**H1**) argues that the type of service (utilitarian vs. hedonic) influences the willingness of individuals to disclose their information; specifically, it is hypothesized that individuals are more likely to give up their data when this loss of privacy is aimed at receiving a personalized recommendation for a utilitarian rather than hedonic service.

The type of service (utilitarian vs. hedonic) also appears to influence the perceived level of expertise of the artificial intelligence in charge of making recommendations.

A recent study by Longoni and Cian (2022) revealed that individuals perceive artificial intelligence as more competent for utilitarian services and humans for hedonic services, as technology is associated with rationality and logic and people with emotions.

Therefore, considering the perceived higher AI competence in utilitarian contexts (Belanche, Casaló, Schepers & Flavián, 2021; Liu, Yi & Wan, 2022), the second hypothesis (**H2**) argues that the utilitarian nature of the service increases the level of Avatar competence perceived by the consumer.

In addition, the level of AI competence perceived by the consumer has an impact on the individual's willingness to disclose their personal information; in fact, two recent studies (Gieselmann & Sassenberg, 2022; Pizzi et al. (2023) have highlighted how consumers are more likely to disclose their personal information in exchange for the enhanced competence offered by AI. This lays the groundwork for the third hypothesis (**H3**), which argues that perceived competence influences, via mediation, the relationship between the type of service for which the Avatar has to provide a recommendation and the willingness of individuals to disclose their personal information; specifically, a higher level of perceived Avatar competence leads to a greater consumer's propensity to disclose their data to receive a personalized recommendation.

The fourth and final hypothesis (**H4**) argues that the sexual gender of the anthropomorphized AI moderates the relationship between the type of service (utilitarian vs. hedonic) and the perceived competence level of the Avatar. Specifically, it is hypothesized that a male Avatar is perceived to be more competent for utilitarian services while a female Avatar is perceived to be more competent for hedonic services.

The latter hypothesis finds its grounding in all the studies that show how humans apply stereotypes related to sexual gender, whereby men and women have differing abilities between them (Prentice & Carranza, 2002; Hentschel et al., 2019; Guo et al., 2020; Brahnam & De Angeli, 2012) also to non-human agents (Epley, Waytz, & Cacioppo, 2007), such as robots and artificial intelligence (Nass, Moon, & Green, 1997; Ernst & Herm-Stapelberg, 2020; Eyssel & Hegel, 2012; Powers & Kiesler, 2006; Powers et al., 2005; Nowak & Fox, 2018; Bastiansen, Kroon & Araujo, 2022).

In particular, the link between sexual gender and higher levels of perceived competence is based on gender stereotypes whereby women are expected to be warm, helpful towards others, and caring, while for men, the expectations are related to their agency, competence, and authority (Ellemers, 2018).

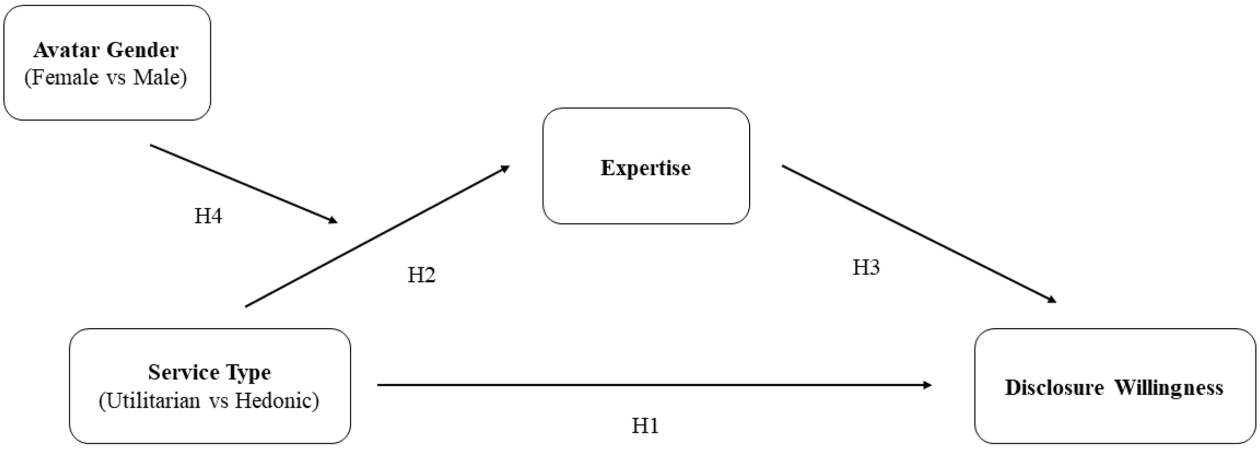
H1: The Utilitarian service type has a more positive impact on the disclosure willingness compared to the hedonic one.

H2: The perceived Avatar expertise mediates the relationship between the service type and the disclosure willingness. The Utilitarian service type (vs Hedonic service type) increases the perceived Avatar expertise by users.

H3: The perceived Avatar expertise mediates the relationship between the service type and the disclosure willingness. A higher perceived Avatar expertise leads to a higher disclosure willingness.

H4: The Avatar Gender moderates the relationship between service type and perceived Avatar expertise. In particular, the female gender related to a hedonic service leads to a higher perceived Avatar expertise, whereas the male gender related to a utilitarian service leads to a higher perceived Avatar expertise.

Taking into account the relationships mentioned above, the following conceptual model has been created:



3. Experimental Research

3.1 Experiment Overview

The primary objective of this study is to investigate the effect that the sexual gender of digital human avatars (female vs. male) has on consumers' perceived level of competence in making highly personalized recommendations for different types of services (hedonic vs. utilitarian), which is also hypothesized to have an impact on consumers' willingness to provide their data to receive such recommendations.

Specifically, this study aims to find confirmation that there is a gender bias against digital human avatars, whereby the sexual gender of digital human avatars moderates the relationship between the type of service recommended (hedonic vs. utilitarian) and the level of expertise perceived by consumers, which in turn mediates consumers' propensity to disclose their personal information to the avatar.

To answer the problem and the research question, this study adopted an online experimental design, which is now considered standard practice due to the ease with which a large number of people can be reached in relatively less time and cost than laboratory and field experiments (Birnbaum, 2004; Hair et al., 2010; Reips, 2000).

However, one disadvantage is not having the same level of control that a laboratory experiment allows.

To validate the stimuli used in the main study, namely type of service (hedonic vs. utilitarian) and sexual gender (female vs. male), a pre-test was initially conducted. Once the pre-test was conducted and it was ascertained that the stimuli were perceived correctly by the respondents, it was possible to proceed with the next step, namely the launch of the final experiment to test the hypotheses developed in Chapter 2.

The study used a 2 (type of service: hedonic vs. utilitarian) x 2 (sexual gender: female vs. male) between-subjects design, in which each respondent was exposed to only one condition in a randomized manner, whereby the chance of being exposed to any treatment was the same for each participant. In this way, carry-over effects were avoided whereby respondents, if exposed to more than one condition, can use what was learned from one condition in the next (Charness et al., 2012). SPSS software (Statistical Package for Social Science) was used to assess the significance of the hypotheses. Specifically, a one-way ANOVA was used to validate H1, while Model Process 4 was used to validate H2 and H3. To validate H4, we used Process Model 7.

3.2 Stimuli Validation: Pretest

The main objective of the pre-test was to assess whether the type of service being studied (hedonic vs. utilitarian) was perceived correctly by respondents (see Appendix A), as well as the sexual gender of the selected digital human avatars, Daniel Kalt and YUMI (see Appendix B).

This initial study was conducted by administering an online questionnaire in English, constructed via Qualtrics XM, and distributed to a non-probabilistic sample, precisely the so-called *'convenience sample'*, where participants were primarily reached via the main social networks (Facebook, Instagram, and WhatsApp) of the personal network of the author of this thesis.

Regarding the size of this pre-test sample, we tried to reach a number greater than or equal to 30 as a study conducted by Perneger et al. (2015) found that samples that are too small (5-15 participants) may fail to detect even the most common problems, whereas instead a sample size of 30 can be considered a reasonable starting point for pre-testing questionnaires as it allows *"a reasonably high power (around 80%) to detect a problem occurring in 5% of the population and to detect the recurrence of a problem affecting 10% of the respondents. At the same time, if for a given question no problem is detected among the 30 respondents, the 90 % two-sided upper confidence limit on the true prevalence of problems is 10 %"* (Perneger et al., 2015, p. 151).

3.2.1 Pretest Design

The pretest consists of a questionnaire, constructed using Qualtrics XM, divided into four parts (see Appendix C).

The initial part consists of an informative introduction for respondents, in which an explanation of the academic purpose of the study is given and full compliance with privacy regulations regarding data collection and management is ensured.

Then, after brief instructions on how to correctly complete the questionnaire, the second part of the survey consisted of a randomized block consisting of two separate scenarios regarding the sexual gender of the Digital Human Avatar (female vs. male), followed by a 7-point Likert scale that required candidates to express their perception of the image across three items (female, male, neutral).

The images of the two Digital Human Avatars were sourced from the paper *"An emerging theory of avatar marketing*" (Miao et al., 2022) while the scale used to assess the perception of sexual gender comes from the work "*Models of (Often) Ambivalent Robot Stereotypes: Content, Structure, and Predictors of Robots' Age and Gender Stereotypes*" by Perugia et al. (2023).

This block was designed to show the candidates only one of the two images of the digital human avatars (YUMI vs. Daniel Kalt) chosen for this study (see Appendix A), to assess the goodness of gender manipulation (female vs. male).

The third part of the pretest is instead aimed at assessing the perception of the type of service and consists of a randomized block consisting of two distinct scenarios concerning the type of service perceived (hedonic vs. utilitarian), followed by the HED/UT differentiated semantic scale.

The texts concerning services were formulated independently, where the choice of utilitarian service is due to the work *"The emotional influence on satisfaction and complaint behavior in hedonic and utilitarian services"* (Calvo-Porral & Otero-Prada, 2021) while the choice of hedonic service is due to two studies: *"Hedonic service consumption and its dynamic effects on sales in the brick-and-mortar retail context"* (Zhou et al, 2023) *and "Verifying the hedonic vs. utilitarian consumer attitudes categorization: the case of spas and salons"* (Hanks & Mattila, 2012).

As for the scale used, it is derived from the work *"Measuring the hedonic and utilitarian dimensions of consumer attitude"* (Voss, Spangenberg, & Grohmann, 2003).

This scale requires participants to describe the service using ten adjectives (five utilitarian and five hedonic) and it is used to determine the nature of hedonic and utilitarian evaluation of products and services.

The final part of the pretest consists of four socio-demographic questions to find out the characteristics that distinguish the sample, namely age, gender, level of education, and occupation.

Once the data had been collected, they were analyzed with the help of the statistical software SPSS (Statistical Package for Social Science).

3.2.1.1 Avatar Gender

Regarding the sexual gender manipulation of digital human avatars, photos of two digital human avatars used today for personalized recommendations were selected (see Appendix B).

The male digital human avatar is represented in this study by Daniel Kalt, a digital human avatar developed by the investment bank UBS that can predict financial data and present investment recommendations to high-level clients.

The female digital human avatar, on the other hand, is represented by YUMI, a digital human avatar developed by the skincare brand SK-II to make highly personalized recommendations to clients.

Again, each respondent was exposed to only one of the two images, randomly.

To measure the perceived sexual gender based on the image the respondents were exposed to, we used a 7-point Likert Scale already used in a study conducted by Perugia et al. (2023) and aimed at investigating the perceived age and sexual gender of the humanoid robots in the ABOT dataset. The scale requires candidates to express their perceptions on three items (feminine, masculine, gender neutral) using a 7-point Likert scale for which the response modes range from completely disagree (=1) to completely agree (=7).

3.2.1.2 Service Type

In general, in the literature on services, scholars distinguish between utilitarian and hedonic services (Pérez, García de los Salmones, & Baraibar-Diez, 2020) where hedonic services provide consumers with values such as excitement and entertainment, while utilitarian services provide consumers with functional utilities or solve practical problems (Andreu, CasadoDíaz & Mattila, 2015).

Several authors agree that banking services are an example of a utilitarian service (e.g. Collier et al., 2014; Dhar & Wertenbroch, 2000; Calvo-Porral & Otero-Prada, 2021) as they are perceived as uninspiring or exciting (Wang & Jiang, 2019), characterized by functional utilities and cognitive benefits, and orientation to things (Stafford, 1995; Kempf, 1999; Pérez, García de los Salmones, & Baraibar-Diez, 2020).

For this reason, the utilitarian service chosen for this study is a banking service, i.e., opening a current account at a bank.

About hedonic service, a study conducted by Zhou et al. (2023) on the consumption of hedonic services particularly highlights three categories of services: entertainment, food, and lifestyle.

Since this study is aimed at investigating the projection of gender stereotypes between men and women on highly anthropomorphized forms of artificial intelligence, and assuming that hedonic services are more related to the female world, the choice fell into the third category of hedonic services, namely lifestyle services.

Lifestyle services include various categories ranging from fitness gyms to beauty salons in shopping malls, and they stimulate physical, sensory, and emotional responses from shoppers (Hanks and Mattila, 2012; Roozen and Katidis, 2019). A confirmation that this type of hedonic service finds women as its main consumers can be found in a study conducted by Hanks and Mattila (2012), who investigated the different perceptions between spas and beauty salons based on a sample of only women. Similarly, a study conducted by Lövei-Kalmár, Jeles, & Ráthonyi (2019) on the habits of spa visitors was based on a sample of 262 visitors, of which 85% of the respondents were women and only 15% were men. The aforementioned study by Hanks and Mattila (2012) found that there is a difference between the perception of spas and salons, whereby the spa experience is considered more hedonic while the experience offered by salons is considered more utilitarian.

For this reason, the hedonic service chosen for this study is the experience offered by the spa.

To assess whether the two types of services (bank account opening service and spa hedonic service) are perceived correctly by the respondents, we devised two conditions: one condition requires the respondent to imagine a situation in which he/she goes to a bank to open a bank account while the other requires the respondent to imagine a situation in which he/she goes to a spa to choose the type of treatment he/she wants to have to treat him/herself to a day of relaxation.

To avoid the carry-over effects (Charness et al., 2012) mentioned above, each respondent was only exposed to one of the two conditions.

To assess the type of service respondents perceive they are dealing with, the HED/UT scale was used. The HED/UT scale is generally applicable, reliable, and valid for measuring the hedonic and utilitarian components of attitudes and it is used to determine the nature of customers' evaluation of products and services and/or their advertising appeals (Voss, Spangenberg, & Grohmann, 2003).

Initially, this differential semantic scale comprised 12 adjectives for the hedonic dimension and 12 adjectives for the utilitarian dimension, assessed by seven response modes (from *completely disagree* to *completely agree)* but being too long, it was later reduced following analyses of item-total correlations, internal consistency (reliability), AVE and unidimensionality, reducing the number of items from 12 to 5 for both variables, as Table V shows.

Table V - HED/UT items: initial and final scale statistics

	Study 1[b]						
	Brand Names			Product Categories			Study 2[c]
Items[a]	*Factor 1*	*Factor 2*	*Item-Total Correlation*	*Factor 1*	*Factor 2*	*Item-Total Correlation*	*Product Categories*
Utilitarian							
Effective/ineffective	.68	.58	.84	.60	.62	.86	.87/.84
Helpful/unhelpful	.66	.59	.80	.58	.61	.84	.89/.86
Functional/not functional	.57	.64	.77	.63	.54	.82	.91/.87
Necessary/unnecessary	.69	.43	.73	.49	.65	.75	.89/.86
Practical/impractical	.58	.54	.75	.51	.63	.75	.89/.86
Beneficial/harmful	.69	.46	.75	.47	.68	.76	
Useful/useless	.74	.34	.73	.46	.66	.73	
Sensible/not sensible	.66	.50	.74	.52	.61	.78	
Efficient/inefficient	.69	.47	.74	.49	.63	.78	
Unproductice/productive	.56	.46	.75	.53	.55	.70	
Handy/not handy	.53	.46	.59	.47	.43	.66	
Problem solving/not problem solving	.44	.56	.57	.61	.56	.66	
Hedonic							
Not fun/fun	−.62	.56	.82	.72	−.48	.84	.98/.85
Dull/exciting	−.70	.46	.72	.61	−.57	.80	.85/.80
Not delightful/delightful	−.61	.56	.79	.69	−.46	.81	.86/.81
Not thrilling/thrilling	−.67	.56	.84	.66	−.51	.80	.82/.77
Enjoyable/unenjoyable	−.62	.45	.71	.63	−.44	.72	.79/.74
Not happy/happy	−.57	.66	.83	.73	−.42	.80	
Unpleasant/pleasant	−.66	.45	.74	.61	−.51	.76	
Not playful/playful	−.58	.64	.82	.62	−.52	.76	
Cheerful/not cheerful	−.60	.51	.75	.69	−.43	.76	
Amusing/not amusing	−.57	.40	.64	.61	−.46	.71	
Not sensuous/sensuous	−.47	.57	.68	.60	−.44	.70	
Not funny/funny	−.39	.52	.60	.63	−.32	.65	
Explained Variance[b]	33%	60%		32%	63%		80%
AVE[d]							
Hedonic		50%			47%		71%
Utilitarian		49%			49%		79%
Reliability[d]							
Hedonic		.92			.91		.95
Utilitarian		.92			.92		.93
Coefficient Alpha							
Hedonic		.95			.95		.95
Utilitarian		.95			.95		.92

3.2.3 Pretest Results

The sample of the population reached by the survey included mainly university students and new employees located in different cities in Italy.

Therefore, following this assumption, the mean age of the respondents was 27 years, although the anagraphic range was between a minimum of 19 years and a maximum of 65 years (see Appendix D.A).

Regarding the gender of the respondents, there was no prevailing gender as men accounted for 50% (21/42), as did women.

To test the success of the manipulation of the independent variable (Service Type), a comparison of averages was conducted by applying four Independent sample T-test as an analysis to test whether or not there was a statistically significant difference between the averages of the groups according to the visual condition to which they were exposed.

After performing the first test, looking at the table of descriptive statistics, it was possible to see that the group of respondents (20 people) exposed to the scene of the utilitarian service, coded with 0, had a mean of 1.7350 while those (22 people) exposed to the condition of the hedonic service, coded with 1, recorded a value of 5.5818 (see Appendix D.B).

Furthermore, considering the Independent sample testing table, a t-test p-value of 0.001 emerged, which was statistically significant (p-value<$\alpha/2$ = 0.025).

Thus, it was possible to see a statistically significant difference between the averages of the groups, confirming the success of the manipulation concerning the independent variable.

With regard to the moderator manipulation check (Avatar Gender), three studies were conducted.

Looking at the descriptive statistics table after the first test for the moderator's manipulation check was complete, it was possible to see that the group of respondents (22 people) exposed to the condition of the Female Avatar, coded with 0, found a mean of 6.95 while those (20 people) exposed to the condition of the Male Avatar, coded with 1, recorded a value of 1.05 to the question of how much (from 1 to 7) the avatar in the picture was "Feminine" (see Appendix D.C).

Furthermore, considering the Independent sample testing table, a t-test p-value of 0.001 emerged, which was statistically significant (p-value$<\alpha/2 = 0.025$).

Therefore, a statistically significant difference between the group averages was found, confirming the success of the manipulation relating to the moderator variable (Gender F) as it was expected that the respondents would consider the scenario representing the female avatar as such.

After the second test related to the manipulation check of the moderator, looking at the table of descriptive statistics, it was possible to note that the group of respondents (22 people) subjected to the scenario related to the Female Avatar, coded with 0, found an average of 1.09 while those (20 people) exposed to the condition of the Male Avatar, coded with 1, recorded a value of 6.70 to the question of how much (from 1 to 7) the avatar in the picture was "Masculine" (see Appendix D.D).

In addition, considering the Independent sample testing table, a p-value for the t-test of 0.001 emerged, which was statistically significant (p-value$<\alpha/2 = 0.025$).

Consequently, a statistically significant difference between the group averages could be observed, confirming the success of the manipulation relating to the moderator variable (Gender M) as it was expected that the respondents would consider the scenario representing the male avatar as such.

After carrying out the third test related to the moderator's manipulation check, looking at the descriptive statistics table, it was possible to note that the group of respondents (22 people) subjected to the scenario related to the Female Avatar, coded with 0, found an average of 1.68 while those (20 people) exposed to the condition of the Male Avatar, coded with 1, recorded a value of 1.30 to the question of how much (from 1 to 7) the avatar in the picture was "Gender Neutral" (see Appendix D.E).

Furthermore, considering the Independent sample testing table, a t-test p-value of 0.077 emerged, which was statistically non-significant (p-value$>\alpha/2 = 0.025$).

Therefore, no statistically significant difference could be found between the group averages, confirming the success of the manipulation relating to the moderating variable (Gender Neutral) as it was not expected that the respondents would consider the two scenarios to be gender neutral.

3.3 Main Study

The present experimental study consists of a conclusive causal research design between subjects 2x2. The results of the study are represented by answers to a questionnaire obtained through a self-administered survey conducted in Italy during the month of August 2023 using the online platform Qualtrics XM.
The aim of this research is to investigate the existence of a gender bias towards a highly anthropomorphized artificial intelligence, e.g. the Digital Human Avatar, whereby one gender is perceived to be more expert than another based on the type of service recommended (utilitarian vs. hedonic). In addition to investigating whether the sexual gender of the digital human avatars moderates the relationship between the type of service recommended (hedonic vs. utilitarian) and the level of expertise perceived by consumers, this study also aims to investigate whether the level of perceived expertise also mediates consumers' propensity to disclose their information to receive personalized recommendations.

3.3.1 Population and Sample

No limits of any kind were placed on the population of this study as personalized recommendations for services can be requested by persons of any age, gender, nationality, education, and professional occupation.
To determine the sample size, we started from the rule of thumb developed by Saeyer and Ball (1981), who conducted a study that showed that at least 30 participants are needed to test an experimental condition. However, to achieve a greater depth of the study, we decided to reach at least 50 respondents per condition. Since this study involves four experimental conditions, we aimed for a sample size of at least 200 participants. As in the case of the pretest, we also used convenience sampling for the main study by drawing from the personal network of the author of the thesis, to reduce data collection costs, and increase efficiency and ease of use (Sekaran & Bougie, 2016). The questionnaire designed via Qualtrics XM was, as the pretest, shared with the study participants via major social networks, such as WhatsApp, Instagram, and Facebook.

3.3.2 Design

As mentioned above, data were collected by means of a questionnaire, which is composed of six main parts (see Appendix E).
At the beginning of the questionnaire, a brief introduction was made with an explanation of the academic purpose of the experimental research. In addition, after including the university's credentials, full compliance with privacy regulations regarding the anonymity policy on data collection and management was ensured.
The second part of the survey is represented by a randomized block made up of two distinct scenarios concerning the gender of the Digital Human Avatar (female vs. male); this block is followed by the relative question deriving from the pretest in which the manipulation check of the moderating variable (Avatar Gender) is verified by asking the subject to describe the avatar with three items (female, male, neutral) by means of a 7-point Likert Scale.

The third part of the survey is represented by a randomized block made up of two distinct scenarios concerning the type of service perceived (hedonic vs. utilitarian); this block is followed by the relative question deriving from the pretest in which the manipulation check of the independent variable (Service Type) is verified by asking the subject to describe the service perceived by him/her in terms of hedonism and utilitarianism using the HED/UT differentiated semantic scale.

Once the pretest was re-proposed within the main study, the fourth part of the survey was represented by a further randomized block consisting of four separate scenarios composed of the combination of the two categorical variables (Avatar Gender and Service Type). In fact, the randomization process was essential within the structure of the questionnaire to obtain a uniform number of exposures to all visual stimuli.

To avoid potential cognitive bias and brand sentiment, all scenarios are represented by mock-ups of service descriptions and Digital Human Avatars.

The fifth part of the survey was introduced to the respondents after being subjected to the observation of one of the four scenarios and this block consists of two scales: the first for the mediator and the second for the dependent variable.

The first scale for the mediator is derived from the scale prevalidated by Ohanian (1990) within the paper "*Construction and Validation of a Scale to Measure Celebrity Endorsers' Perceived Expertise, Trustworthiness, and Attractiveness*", the result of which is a multidimensional semantic differential scale, in which each of the three dimensions on which the source's credibility depends (expertise, trustworthiness, and attractiveness) is measured by five semantic differential items, assessed on 7-point scales.

As this research project examines only one of the three dimensions, the Ohanian scale was readjusted according to the needs of the experimental research, taking into consideration only the five items related to perceived expertise.

As far as the second scale relating to the dependent variable is concerned, it is derived from the scale prevalidated by Collins and Miller (1994) in their work "*Self-Disclosure and Liking: A Meta-Analytic Review*" and later taken up by Cho (2006) in his study "*The Mechanism of Trust and Distrust Formation and Their Relational Outcomes*".

Finally, the sixth and last part of the questionnaire is characterized by the block dedicated to socio-demographic questions, in which respondents were asked about their age, gender, level of education, and occupation.

3.4 Experimental Results

3.4.1 Data Analysis

The data collected through the survey questionnaire generated on Qualtrics XM were exported to the statistical software SPSS (Statistical Package for Social Science) for analysis.

Initially, it was decided to perform a factor analysis to examine and validate the items of the scales used in the conceptual model; in particular, principal component analysis was performed as the means of extraction, and

Varimax as the method of rotation (see Appendix F.A). To decide how many factors to extract, the total explained variance table was observed, verifying that, according to Kaiser's rule, the eigenvalues were greater than 1 and that the cumulative variance as a percentage was greater than 60%.
In addition, both the communality table and the component matrix were observed.
Specifically, all items had an extraction value greater than 0.5 and a loading score greater than 0.3.
Therefore, it was decided to keep all items composing the scales, validating them.
After validating all the scales, a reliability test was carried out to verify the level of reliability of the scales taken into consideration. In particular, the Cronbach's Alpha value of all constructs was observed and accepted to be greater than 60% (see Appendix F.B).
For the manipulation check scale of the independent variable (Service Type), a value of 0.992 was found, for the mediator scale (Expertise) was found a value of 0.997, and for the scale concerning the dependent variable (Disclosure Willingness), a value of 0.990 was recorded. Therefore, all scales were found to be reliable.
In addition, the KMO (Kaiser-Meyer-Olkin) test for measuring the adequacy of sampling was performed. Regarding the scale concerning the manipulation check of the independent variable (Service Type), a value of 0.936 was found, for the mediator scale (Expertise) was found a value of 0.920, and with regard to the scale concerning the dependent variable (Disclosure Willingness), a value of 0.766 was recorded.
Thus, the level of adequacy was more than adequate in all cases.
The Bartlett's sphericity test was then performed, which was statistically significant, finding in all cases a p-value of 0.000 ($p\text{-value} < \alpha = 0.05$).
Regarding the composition of the sample subjected to the main study, the sample of the population included mainly university students and new employees located in different cities in Italy, as for the pretest (see Appendix F.C).
Consequently, following this assumption, the average age of the respondents was 25 years, although the age range was from a minimum of 19 years to a maximum of 65 years.
About the gender of the respondents, men accounted for 49.8% of the sample (106 people), women accounted for 48.4% (103 people) and 1.9% (4 people) of the sample preferred not to specify their sexual gender.

3.4.2 Hypotheses Results

After conducting both factor analysis and reliability tests, the main hypotheses of the conceptual research model were analyzed to confirm or reject its statistical significance and thus its relative success.
To test the significance of the conceptual model's direct hypothesis (H1), a comparison of averages was conducted by applying a One-Way ANOVA (see Appendix F.D) as an analysis to test the effect of the independent variable (Service Type) against the dependent variable (Disclosure Willingness).
Specifically, the independent variable (X) has a nominal categorical nature and is divided into two distinct conditions, coded 0 (hedonic) and 1 (utilitarian), while the dependent variable (Y) has a metric nature. After carrying out the ANOVA, and observing the descriptive statistics table, it was possible to note that the group

of respondents subjected to the scenario coded with 0 (105 people) recorded an average value of 2.8032 while those subjected to the visual condition coded with 1 (108 people) recorded an average value of 5.4198.

Furthermore, considering the ANOVA table, a p-value relative to the F-test of 0.001 emerged, which was statistically significant (p-value$<\alpha = 0.05$).

Therefore, a statistically significant difference between the group averages could be seen, confirming the effect of X on Y. Thus, the direct hypothesis H1 (main effect) was proven.

To test the significance of the moderating hypothesis of the conceptual model, a comparison between averages was conducted by applying a Two-Way ANOVA (see Appendix F.E) to test the joint effect of the independent variable (Service Type) and the moderating variable (Avatar Gender) against the mediating variable (Expertise).

Specifically, the independent variable (X) and the moderator (W) are nominal categorical in nature and are both distinct conditions coded with 0 (hedonic; female) and 1 (utilitarian; male), while the mediator variable (M) is metric in nature.

After carrying out the ANOVA, looking at the table of descriptive statistics, it was possible to note that the group of respondents (52 people) subjected to the scenario coded with 0,0 (hedonic; female) recorded a mean value of 3.8846, the subjects (53 people) subjected to the visual condition coded with 0,1 (hedonic; male) recorded a mean value of 1. 6906, the group of respondents (54 people) subjected to the visual condition coded with 1,0 (utilitarian; female) showed a mean value of 4.2370 while the subjects (54 people) subjected to the visual condition coded with 1,1 (utilitarian; male) showed a mean value of 6.7815.

Furthermore, considering the Test of between subjects table, a p-value relating to the corrected model of 0.001 emerged, which was statistically significant (p-value$<\alpha = 0.05$), noting the existence of model fit.

Specifically, all effects of the independent variables (X, W, and X*W) on the mediator (M) were examined.

The first direct effect between the independent variable and the mediator (X - M) showed a p-value of 0.001.

Regarding the second direct effect between the moderator and the mediator (W - M), a p-value of 0.141 emerged, while with regard to the joint interaction effect between the independent variable and the moderator towards the moderator (X*W - M), a p-value of 0.001 emerged, thus demonstrating the success of the interaction effect.

Thus, the moderation hypothesis H4 (interaction effect) was proven, as can be seen from the Interaction Plot in which a disordinal interaction with crossover is shown.

To test the significance of the indirect hypotheses of the conceptual model, a regression analysis was conducted by applying the Process Macro Version 4.0 model 4 developed by Andrew F. Hayes, so as to test the direct and mediating effect (see Appendix F.F).

In order to test the success of each effect, it was necessary to distinguish between three different relationships: a first effect between the independent variable and the dependent variable (H1), a second effect between the independent variable and the mediator (H2) and a third effect between the mediator and the dependent variable (H3).

Regarding the direct effect between X and Y (H1), through observation of the SPSS output, it was possible to observe a p-value equal to 0.4387, an adverse confidence interval (LLCI= -0.0970; ULCI= 0.2229) and a positive regression coefficient β equal to 0.0629. Therefore, this effect was not statistically significant, not confirming H1 (main effect).

With regard to the first section of the indirect effect between X and M (H2), through the examination of the SPSS results, a p-value of 0.0000, a favorable confidence interval (LLCI=0.3342; ULCI=3.1301) and a positive regression coefficient β of 2.7321 were observed. Therefore, this effect was statistically significant, confirming H2 (the first part of the indirect effect).

Moving on to the second section of the indirect effect between M and Y (H3), through the observation of the SPSS output, it was possible to observe a p-value equal to 0.0000, a favorable confidence interval (LLCI=0.8948; ULCI=0.9746) and a positive regression coefficient β equal to 0.9347. Therefore, this effect was statistically significant, confirming H3 (the second part of the indirect effect).

Considering the results, as both sections of the indirect effect were statistically significant, whereas the direct effect was not, it was possible to confirm the success at the global level of the mediation effect (indirect effect), finding full mediation.

In order to test the significance of all hypotheses of the conceptual model, a regression analysis was conducted by applying the Process Macro Version 4.0 model 7 developed by Andrew F. Hayes, so as to test the direct, mediating, and moderating effect of the research (see Appendix F.G).

In order to test the success of each effect, it was necessary to distinguish them into four different relationships: a first effect between the independent variable and the dependent variable (H1), a second effect between the independent variable and the mediator (H2), a third effect between the mediator and the dependent variable (H3) and a fourth and final joint effect between the moderator and the independent variable towards the mediator (H4).

Regarding the direct effect between X and Y (H1), through observation of the SPSS output, it was possible to observe a p-value equal to 0.4387, an adverse confidence interval (LLCI= -0.0970; ULCI= 0.2229) and a positive regression coefficient β equal to 0.0629. Therefore, this effect was not statistically significant, not confirming H1 (main effect).

With regard to the first section of the indirect effect between X and M (H2), through the examination of the SPSS results, it was possible to observe a p-value equal to 0.0374, a favorable confidence interval (LLCI=0.0208; ULCI=0.6840) and a positive regression coefficient β equal to 0.3524. Therefore, this effect was statistically significant, confirming H2 (the first part of the indirect effect).

Moving on to the second section of the indirect effect between M and Y (H3), through the observation of the SPSS output, it was possible to observe a p-value equal to 0.0000, a favorable confidence interval (LLCI=0.8948; ULCI=0.9746) and a positive regression coefficient β equal to 0.9347. Therefore, this effect was statistically significant, confirming H3 (the second part of the indirect effect).

Finally, regarding the interaction effect between X and W with respect to M (H4), through the observation of the SPSS output, it was possible to observe a p-value equal to 0.0000, a favorable confidence interval

(LLCI=4.2707; ULCI=5.2063) and a positive regression coefficient β equal to 4.7385. Therefore, this effect was also statistically significant, confirming H4 (interaction effect).

In the light of the results obtained, it was possible to confirm the further success of the double check carried out by means of Model 7, demonstrating both a full mediation (a phenomenon that occurs when the two sections of the indirect effect are statistically significant regardless of the direct effect between X and Y) and a significant interaction effect.

Prior to the overall success of the main test, validation of the visual stimuli was again carried out by performing the manipulation check relative to the pre-test, for both the independent variable and the moderator variable.

3.5 General Discussion and Conclusion

This study set out to investigate whether the sexual gender attributed to highly anthropomorphized forms of artificial intelligence, such as Digital Human Avatars, moderates the relationship between the type of service recommended (hedonic vs. utilitarian) and the level of competence perceived by consumers. In addition to the moderating effect of the sexual gender of the Digital Human Avatars, this study set out to investigate whether the level of competence of the Digital Human Avatars perceived by consumers influences, via mediation, their propensity to disclose personal information useful for receiving the recommendation.

To find an answer to the questions underlying this research, a questionnaire was administered to a non-probabilistic sample, the so-called convenience sample, using Qualtrics XM.

The questionnaire was structured in such a way as to expose the respondents to only one of the four elaborated conditions, the outcome of the combination of the two categorical variables, namely the sexual gender of the avatar (female vs. male) and the type of service recommended (hedonic vs. utilitarian).

The elaboration of these four conditions is aimed at understanding whether consumers perceive one sexual gender as more likely to recommend a particular type of service than another; specifically, this research sought to investigate whether male digital human avatars are considered more likely to recommend utilitarian services and female digital human avatars more likely to recommend hedonic services.

Following the analysis of the data using the statistical tool SPSS, it was found that the propensity to disclose personal information to receive a personalized recommendation is greater when the service to be recommended is utilitarian (H1). The greater propensity to give out one's data when the service is utilitarian can be traced back to the fact that these types of services, unlike hedonic services, are perceived as more necessary.

The type of service was also shown to have an influence on the level of perceived competence of the Avatar, which was found to be higher when the service to be recommended was utilitarian (H2).

The level of perceived Avatar competence is quite relevant in this study as it influences (via mediation) the propensity of consumers to disclose their information.

Indeed, data analysis confirmed that when perceived competence levels are higher, users are more likely to disclose their information to receive the recommendation (H3). In other words, users are more likely to give up their information when they perceive that the person to whom they are giving their information is competent and able to provide an optimal personalized recommendation. However, this study was designed to detect whether gender stereotypes that influence human relationships are also unconsciously projected onto non-human agents. In fact, the fourth and final hypothesis that was confirmed following the data analysis found that the sexual gender attributed to Digital Human Avatars for anthropomorphization purposes influences (through moderation) the relationship between the type of service to be recommended to users and the level of perceived competence of the Avatar (H4), i.e. male Avatars are preferred by users when the service to be recommended is utilitarian while female Avatars are preferred when the service to be recommended is hedonic.

3.5.1 Theoretical and Practical Implications

From a theoretical point of view, this study set out to address the need to pay more attention to the effects of sexual gender attribution on artificial intelligence that has been raised by several scholars (Alabed, Javornik & Gregory-Smith, 2022; Diederich et al., 2022; West et al., 2019).

This goal was also recently pursued by Jungyong Ahn, Jungwon Kim, and Yongjun Sung (2022), who investigated the effects that gender stereotypes, the outcome of assigning a sexual gender to chatbots, have on consumers' evaluations of recommendations for utilitarian and hedonic products. The aforementioned authors, together with Pizzi et al. (2021), however, emphasized the importance of focusing not only on products but also on services, which is why this thesis considered utilitarian and hedonic services.

The positive outcome of this study has in fact made it possible to confirm that the attribution of a sexual gender to anthropomorphized forms of artificial intelligence has an impact on the perception of their competence not only when the recommendations pertain to material products but also to services.

Finding evidence of the fact that male Avatars are perceived to be more competent for utilitarian service recommendations while female Avatars are perceived to be more competent for hedonic services is further confirmation of what other scholars have already found in the past, i.e. that the attribution of a sexual gender to forms of technology such as robots (Eyssel & Hegel, 2012) or chatbots (Fox & Nowak, 2018) results in the activation of gender stereotypes in consumers, which leads them to expect from these technological forms skills differentiated according to the particular sexual gender that has been attributed to them (e. g. Bastiansen, Kroon, & Araujo, 2022; Nass & Moon, 2000) as gender stereotypes are based on the assumption that men and women have different skills.

In fact, Ellemers (2018) argues that women are ascribed more emotional qualities (e.g. caring, helpful, and warm) while men are ascribed dominance characteristics (e.g. authority, competence, and agency). Since the consumption of hedonic services is predominantly affective whereas utilitarian consumption is predominantly cognitive (Crowley, Spangenberg & Hughes, 1991; Holbrook, 1994; Botti & McGill, 2011), the fact that this study found that male avatars are preferred for utilitarian recommendations whereas female avatars are preferred for hedonic recommendations is a confirmation of the fact that the level of perceived competence varies according to task type.

In addition to sexual gender, the type of service itself was found to influence the level of perceived competence in that, although female avatars were perceived to be more competent than male avatars in processing a personalized recommendation for a hedonic service, perceived competence levels were on average higher when the recommendations were for utilitarian services. This represents a confirmation that consumers perceive AI-powered technology as more competent to process recommendations of a utilitarian nature, confirming what authors such as Longoni and Cian (2022), or Belanche, Casaló, Schepers, and Flavián (2021) have already found.

The degree to which an Avatar is perceived as competent was found to have a mediating effect between the type of service and the consumers' propensity to disclose their information. In fact, the perceived expertise of the Avatar is very important for the purposes of the recommendation as this study found that a higher perception of expertise (influenced by both the type of service and the moderating effect played by the Avatar's sexual gender) leads to a higher propensity of consumers to disclose their information, thus confirming the relationship between expertise and disclosure willingness previously found by other authors in their studies (Gieselmann & Sassenberg, 2022; Pizzi et al., 2023).

The willingness to disclose one's data is functional for recommendation purposes since it is because of the data provided by users that recommendation systems can formulate personalized recommendations and this willingness to disclose was found to be influenced both by the perceived expertise of the avatar and by the type of service to be recommended.

As a matter of fact, utilitarian services are characterized by a functional character that leads them to be conceived as more necessary than a hedonic service that is instead seen more as an end in itself and, in line with this, the data analysis of this study found that consumers give up more of their data in order to receive personalized recommendations for utilitarian services, confirming what other authors have found in the past (Culman & Amstrong, 1999; Kraft et al., 2017; Robinson, 2017; Smith et al., 2011; Plangger & Montecchi, 2020).

As far as practical implications are concerned, this study differs from the one conducted in 2022 by Jungyong Ahn, Jungwon Kim, and Yongjun Sung not only for focusing on services and not goods but also for taking as the object of study not chatbots but a form of technology powered by highly anthropomorphized artificial intelligence, the Digital Human Avatars. In fact, the major managerial contribution of this study was to investigate the factors that contribute to influencing the effectiveness of this recent form of technology that, considering the future relevance of virtual realities such as the Metaverse, is set to flourish in the coming years (Emergen Research, 2023).

By demonstrating that the sexual gender attributed to the Digital Human Avatar influences the degree to which it is perceived to be competent according to the type of service to be recommended, this study offers marketers who want to make use of this highly anthropomorphized form of technology a cue on the basis of which they can better adapt the anthropomorphic design of the Avatar to the expectations of consumers according to the type of service they offer, in order to improve its effectiveness.

3.5.2 Limitations and Future Research

This study set out to investigate the existence of gender bias towards highly anthropomorphized forms of technology, i.e. Digital Human Avatars.

However, due to budget limitations and the impossibility of using a suitable structure to subject the respondents to different types of stimuli, this study could not show the sample members a Digital Human Avatar at its full potential.

Digital Human Avatars are characterized by the fact that they are highly realistic in both form and behavior. They present an astonishing intelligence both cognitively and emotionally, which is why they, unlike other avatars, can communicate with humans through both verbal and non-verbal communication. Nevertheless, as the right tools were not available, it was not possible to show the respondents of the questionnaire an avatar in 3D form, nor was it possible to create a form of interaction between them.

The highly anthropomorphized appearance was communicated to the respondents visually with the help of an image, while their intellectual potential was reported to the subjects by means of a brief description above the avatar image.

In light of the relevance that these avatars may have for companies in virtual realities such as the Metaverse, it is good that future studies that have the necessary means try to investigate the effects of the human characteristics attributed to these avatars, such as sexual gender, by providing the right context, i.e. within these virtual realities in which these avatars would then be used. This would expose consumers to a Digital Human Avatar to the fullest extent of its capabilities and provide contextualized results.

In addition, sexual gender is only one of the human characteristics that are attributed to technology to anthropomorphize it, and, in fact, future studies should investigate whether characteristics such as age or race attributed to the Avatar are also able to bring out bias, influencing consumer perception.

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Appendices

Appendix A: Stimulus Material for the Pretest (Independent Variable)

Figure A.1 – Utilitarian service

Description_U

Imagine that you want to open a **current account** at a bank and request assistance in order to compare the different offers to assess the best option in terms of costs and services of the accounts included (such as salary/pension credit, cheques, transfers, bill payment, debit card, credit card).

Figure A.2 – Hedonic service

Description_H

Imagine you want to spend a **day of wellness** at a spa. In order to choose the best option, you ask for assistance in comparing the different services and treatments the spa offers (such as massage, hydrotherapy, sea salt scrub, emotional shower, Turkish bath, sauna)

Appendix B: Stimulus Material for the Pretest (Moderator)

Figure B.1 – Daniel Kalt (Male Avatar)

Figure B.2 – YUMI (Female Avatar)

Appendix C: Pretest Design

Introduction

Hi everyone! My name is Arianna Minnetti and I am a student of the Master's course in Marketing at Luiss Guido Carli University. I am working on my thesis project, which aims to investigate the effectiveness of digital human avatars in recommending different types of services. Only a limited number of people will take part in this study, hence YOUR opinion on this topic is very important for the success of the project. Your answers will be COMPLETELY ANONYMOUS. Your name and the single answers will not be shared with anyone.

Instructions

You will see the image of a Digital Human Avatar and you will be asked to answer one question about it.

Randomized exposure to one of two scenarios

Look carefully at the image below

Look carefully at the image below

1st Set of Questions (Avatar Gender Manipulation Check)

How would you describe the Digital Human Avatar in the image?

	Completely Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Completely Agree
Feminine	O	O	O	O	O	O	O
Masculine	O	O	O	O	O	O	O
Gender neutral	O	O	O	O	O	O	O

Second instructions

You will read a short description of a situation in which you want to purchase a particular type of service and will be asked to answer one question about it.

Randomized exposure to one of two scenarios

Description_U

Imagine that you want to open a **current account** at a bank and request assistance in order to compare the different offers to assess the best option in terms of costs and services of the accounts included (such as salary/pension credit, cheques, transfers, bill payment, debit card, credit card).

Description_H

Imagine you want to spend a **day of wellness** at a spa. In order to choose the best option, you ask for assistance in comparing the different services and treatments the spa offers (such as massage, hydrotherapy, sea salt scrub, emotional shower, Turkish bath, sauna)

2nd Set of Questions (Service Type Manipulation Check)

Based on the above description, how would you describe the service you want to purchase?

Necessary	○	○	○	○	○	○	○	Unnecessary
Effective	○	○	○	○	○	○	○	Ineffective
Functional	○	○	○	○	○	○	○	Not functional
Practical	○	○	○	○	○	○	○	Impractical
Helpful	○	○	○	○	○	○	○	Unhelpuful
Dull	○	○	○	○	○	○	○	Exciting
Not delightful	○	○	○	○	○	○	○	Delightful
Not fun	○	○	○	○	○	○	○	Fun
Not thrilling	○	○	○	○	○	○	○	Thrilling
Boring	○	○	○	○	○	○	○	Interesting

Third instructions

We're almost done. I will now ask you some questions about yourself. Please read each of the following questions carefully and select the answer that suits you best.

3rd Set of Questions (Socio-Demographic Questions)

What is your age?

What is your gender?

- ○ Male
- ○ Female
- ○ Non-binary / third gender
- ○ Prefer not to say

What is your degree of Education?

- Primary school
- Middle school
- Secondary school
- Bachelor's degree
- Master's degree
- PhD. / equilavents

What is your occupation?

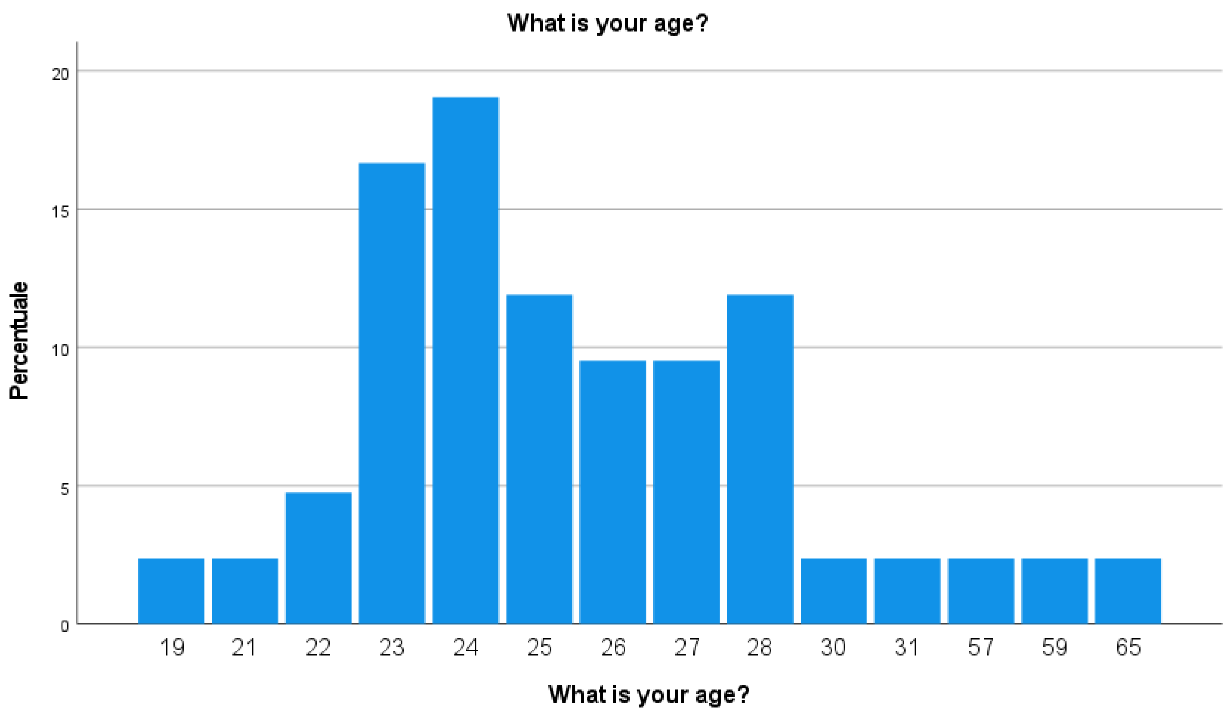
- Unemployed
- Student
- Working student
- Employee
- Self-employed worker

Appendix D: Pretest Results

A. Sample Structure

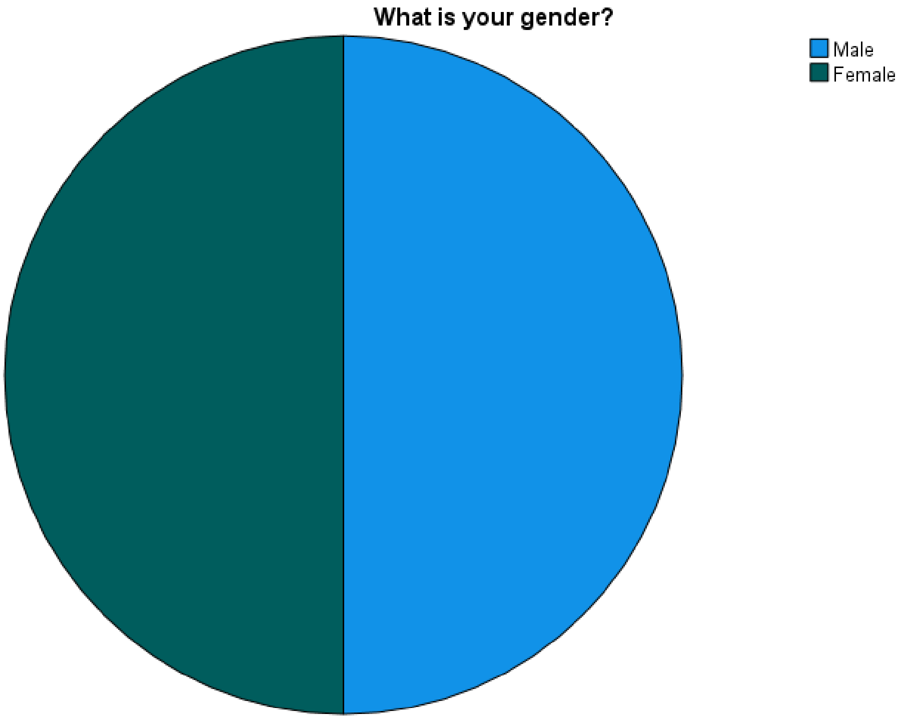
What is your age?

		Frequenza	Percentuale	Percentuale valida	Percentuale cumulativa
Valido	19	1	2,4	2,4	2,4
	21	1	2,4	2,4	4,8
	22	2	4,8	4,8	9,5
	23	7	16,7	16,7	26,2
	24	8	19,0	19,0	45,2
	25	5	11,9	11,9	57,1
	26	4	9,5	9,5	66,7
	27	4	9,5	9,5	76,2
	28	5	11,9	11,9	88,1
	30	1	2,4	2,4	90,5
	31	1	2,4	2,4	92,9
	57	1	2,4	2,4	95,2
	59	1	2,4	2,4	97,6
	65	1	2,4	2,4	100,0
	Totale	42	100,0	100,0	



What is your gender?

		Frequenza	Percentuale	Percentuale valida	Percentuale cumulativa
Valido	Male	21	50,0	50,0	50,0
	Female	21	50,0	50,0	100,0
	Totale	42	100,0	100,0	



B. Independent sample T-test (Independent Variable Manipulation Check)

Statistiche gruppo

	IV	N	Media	Deviazione std.	Errore standard della media
MCX	1,00	22	5,5818	,79321	,16911
	,00	20	1,7350	,85611	,19143

Test campioni indipendenti

		Test di Levene per l'eguaglianza delle varianze		Test t per l'eguaglianza delle medie							
						Significatività				Intervallo di confidenza della differenza di 95%	
		F	Sign.	t	gl	P unilaterale	P bilaterale	Differenza della media	Differenza errore std.	Inferiore	Superiore
MCX	Varianze uguali presunte	,007	,934	15,116	40	<,001	<,001	3,84682	,25448	3,33249	4,36115
	Varianze uguali non presunte			15,060	38,830	<,001	<,001	3,84682	,25543	3,33009	4,36355

C. Independent sample T-test (Avatar Gender Manipulation Check – Gender F)

Statistiche gruppo

	MOD	N	Media	Deviazione std.	Errore standard della media
How would you describe the Digital Human Avatar in the image? - Feminine	1,00	20	1,05	,224	,050
	,00	22	6,95	,213	,045

Test campioni indipendenti

		Test di Levene per l'eguaglianza delle varianze		Test t per l'eguaglianza delle medie							
						Significatività				Intervallo di confidenza della differenza di 95%	
		F	Sign.	t	gl	P unilaterale	P bilaterale	Differenza della media	Differenza errore std.	Inferiore	Superiore
How would you describe the Digital Human Avatar in the image? - Feminine	Varianze uguali presunte	,018	,893	-87,584	40	<,001	<,001	-5,905	,067	-6,041	-5,768
	Varianze uguali non presunte			-87,380	39,174	<,001	<,001	-5,905	,068	-6,041	-5,768

D. Independent sample T-test (Avatar Gender Manipulation Check – Gender M)

Statistiche gruppo

	MOD	N	Media	Deviazione std.	Errore standard della media
How would you describe the Digital Human Avatar in the image? - Masculine	1,00	20	6,70	1,129	,252
	,00	22	1,09	,294	,063

Test campioni indipendenti

		Test di Levene per l'eguaglianza delle varianze		Test t per l'eguaglianza delle medie							
						Significatività				Intervallo di confidenza della differenza di 95%	
		F	Sign.	t	gl	P unilaterale	P bilaterale	Differenza della media	Differenza errore std.	Inferiore	Superiore
How would you describe the Digital Human Avatar in the image? - Masculine	Varianze uguali presunte	3,004	,091	22,511	40	<,001	<,001	5,609	,249	5,105	6,113
	Varianze uguali non presunte			21,570	21,347	<,001	<,001	5,609	,260	5,069	6,149

E. Independent sample T-test (Avatar Gender Manipulation Check – Gender N)

Statistiche gruppo

	MOD	N	Media	Deviazione std.	Errore standard della media
How would you describe the Digital Human Avatar in the image? - Gender neutral	1,00	20	1,30	,571	,128
	,00	22	1,68	1,041	,222

Test campioni indipendenti

		Test di Levene per l'eguaglianza delle varianze		Test t per l'eguaglianza delle medie							
						Significatività		Differenza della media	Differenza errore std.	Intervallo di confidenza della differenza di 95%	
		F	Sign.	t	gl	P unilaterale	P bilaterale			Inferiore	Superiore
How would you describe the Digital Human Avatar in the image? - Gender neutral	Varianze uguali presunte	4,986	,031	-1,452	40	,077	,154	-,382	,263	-,913	,150
	Varianze uguali non presunte			-1,491	33,185	,073	,145	-,382	,256	-,903	,139

Appendix E: Main Study Design

Introduction

Hi everyone! My name is Arianna Minnetti and I am a student of the Master's course in Marketing at Luiss Guido Carli University. I am working on my thesis project, which aims to investigate the effectiveness of digital human avatars in recommending different types of services. Only a limited number of people will take part in this study, hence YOUR opinion on this topic is very important for the success of the project. Your answers will be COMPLETELY ANONYMOUS. Your name and the single answers will not be shared with anyone.

Instructions

You will see the image of a Digital Human Avatar and you will be asked to answer one question about it.

Randomized exposure to one of two scenarios

Look carefully at the image below

Look carefully at the image below

1st Set of Questions (Avatar Gender Manipulation Check)

How would you describe the Digital Human Avatar in the image?

	Completely Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Completely Agree
Feminine	○	○	○	○	○	○	○
Masculine	○	○	○	○	○	○	○
Gender neutral	○	○	○	○	○	○	○

Second instructions

You will read a short description of a situation in which you want to purchase a particular type of service and will be asked to answer one question about it.

Randomized exposure to one of two scenarios

Description_U

Imagine that you want to open a **current account** at a bank and request assistance in order to compare the different offers to assess the best option in terms of costs and services of the accounts included (such as salary/pension credit, cheques, transfers, bill payment, debit card, credit card).

Description_H

Imagine you want to spend a **day of wellness** at a spa. In order to choose the best option, you ask for assistance in comparing the different services and treatments the spa offers (such as massage, hydrotherapy, sea salt scrub, emotional shower, Turkish bath, sauna)

2nd Set of Questions (Service Type Manipulation Check)

Based on the above description, how would you describe the service you want to purchase?

Necessary	○	○	○	○	○	○	○	Unnecessary
Effective	○	○	○	○	○	○	○	Ineffective
Functional	○	○	○	○	○	○	○	Not functional
Practical	○	○	○	○	○	○	○	Impractical
Helpful	○	○	○	○	○	○	○	Unhelpuful
Dull	○	○	○	○	○	○	○	Exciting
Not delightful	○	○	○	○	○	○	○	Delightful
Not fun	○	○	○	○	○	○	○	Fun
Not thrilling	○	○	○	○	○	○	○	Thrilling
Boring	○	○	○	○	○	○	○	Interesting

Third instructions

<u>Now the second part of this study begins.</u>

You will read the description of a situation where you will be assisted by a Digital Human Avatar to purchase a particular type of service. Please read carefully.

Randomized exposure to one of four scenarios

Imagine you want to open a **current account**. You go to a bank that provides you with Daniel, a Digital Human Avatar who can understand your verbal and non-verbal language in order to interact with you. Daniel's job is to help you find the type of current account that best suits you based on your needs and requirements.

Imagine you want to spend a day in **wellness**. You go to a spa that provides you with Daniel, a Digital Human Avatar who can understand your verbal and non-verbal language in order to interact with you. Daniel's job is to help you find the treatment that suits you best based on your needs and requirements.

Imagine you want to open a **current account.** You go to a bank that provides you with Yumi, a Digital Human Avatar who can understand your verbal and non-verbal language in order to interact with you. Yumi's job is to help you find the type of current account that best suits you based on your needs and requirements.

Imagine you want to spend a day in **wellness**. You go to a spa that provides you with Yumi, a Digital Human Avatar who can understand your verbal and non-verbal language in order to interact with you.
Yumi's job is to help you find the treatment that suits you best based on your needs and requirements.

3rd Set of Questions (Expertise Questions)

Based on the situation you have just read about, how would you describe the Digital Human Avatar in charge of assisting you in purchasing the service?

Not an expert	○	○	○	○	○	○	○	Expert
Inexperienced	○	○	○	○	○	○	○	Experienced
Unknowledgeable	○	○	○	○	○	○	○	Knowledgeable
Unqualified	○	○	○	○	○	○	○	Qualified
Unskilled	○	○	○	○	○	○	○	Skilled

4th Set of Questions (Disclosure Willingness Questions)

Based on the same description, please indicate how much you agree with the following statements:

	Completely Disagree	Disagree	Somewhat disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Completely Agree
I am willing to provide my personal information when asked by this Digital Human Avatar	○	○	○	○	○	○	○
I am willing to disclose even sensitive personal information to this Digital Human Avatar	○	○	○	○	○	○	○
I am willing to be truthful in revealing my personal information to this Digital Human Avatar	○	○	○	○	○	○	○

Fourth instructions

We're almost done. I will now ask you some questions about yourself. Please read each of the following questions carefully and select the answer that suits you best.

5th Set of Questions (Socio-Demographic Questions)

What is your age?

What is your gender?

- Male
- Female
- Non-binary / third gender
- Prefer not to say

What is your degree of Education?

- Primary school
- Middle school
- Secondary school
- Bachelor's degree
- Master's degree
- PhD. / equilavents

What is your occupation?

- Unemployed
- Student
- Working student
- Employee
- Self-employed worker

Appendix F: Main Study Results

A. Factorial Analysis

A.A HED/UT Scale

Test di KMO e Bartlett

Misura di Kaiser-Meyer-Olkin di adeguatezza del campionamento.		,936
Test della sfericità di Bartlett	Appross. Chi-quadrato	5744,664
	gl	45
	Sign.	,000

Comunalità

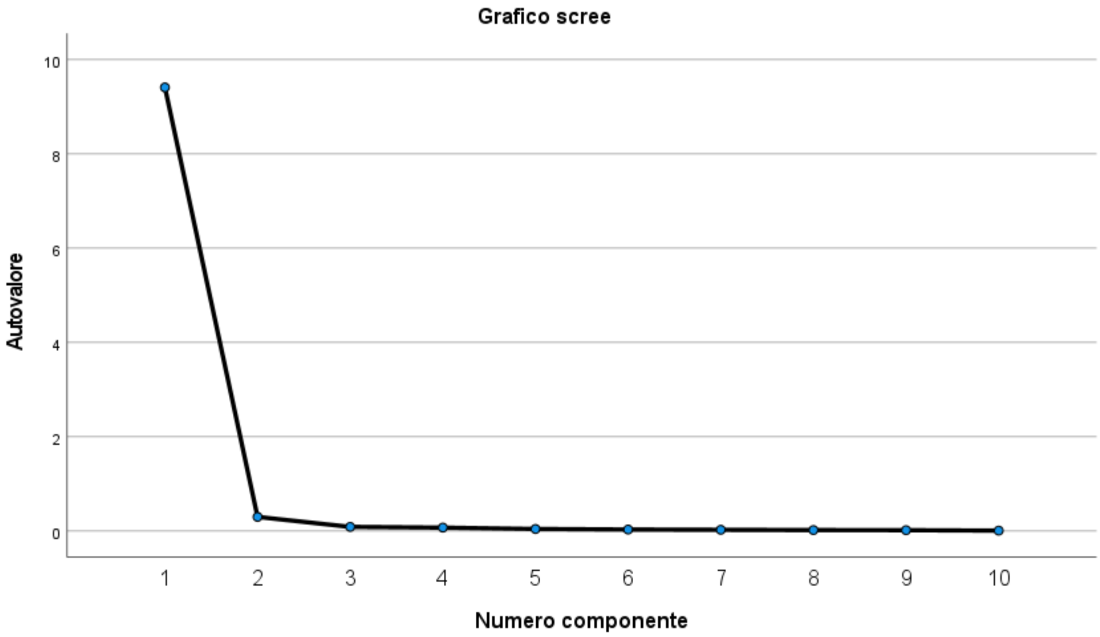
	Iniziale	Estrazione
Based on the above description, how would you describe the service you want to purchase? - Necessary:Unnecessary	1,000	,930
Based on the above description, how would you describe the service you want to purchase? - Effective:Ineffective	1,000	,924
Based on the above description, how would you describe the service you want to purchase? - Functional:Not functional	1,000	,950
Based on the above description, how would you describe the service you want to purchase? - Practical:Impractical	1,000	,929
Based on the above description, how would you describe the service you want to purchase? - Helpful:Unhelpuful	1,000	,926
Based on the above description, how would you describe the service you want to purchase? - Dull: Exciting	1,000	,950
Based on the above description, how would you describe the service you want to purchase? - Not delightful:Delightful	1,000	,956
Based on the above description, how would you describe the service you want to purchase? - Not fun:Fun	1,000	,953
Based on the above description, how would you describe the service you want to purchase? - Not thrilling:Thrilling	1,000	,950
Based on the above description, how would you describe the service you want to purchase? - Boring: Interesting	1,000	,942

Metodo di estrazione: Analisi dei componenti principali.

Varianza totale spiegata

Componente	Autovalori iniziali			Caricamenti somme dei quadrati di estrazione		
	Totale	% di varianza	% cumulativa	Totale	% di varianza	% cumulativa
1	9,409	94,092	94,092	9,409	94,092	94,092
2	,298	2,979	97,071			
3	,086	,862	97,933			
4	,071	,706	98,638			
5	,042	,416	99,054			
6	,030	,297	99,351			
7	,024	,241	99,592			
8	,018	,181	99,772			
9	,016	,160	99,932			
10	,007	,068	100,000			

Metodo di estrazione: Analisi dei componenti principali.



Matrice dei componenti[a]

	Componente 1
Based on the above description, how would you describe the service you want to purchase? - Necessary:Unnecessary	,965
Based on the above description, how would you describe the service you want to purchase? - Effective:Ineffective	,961
Based on the above description, how would you describe the service you want to purchase? - Functional:Not functional	,974
Based on the above description, how would you describe the service you want to purchase? - Practical:Impractical	,964
Based on the above description, how would you describe the service you want to purchase? - Helpful:Unhelpuful	,963
Based on the above description, how would you describe the service you want to purchase? - Dull: Exciting	,975
Based on the above description, how would you describe the service you want to purchase? - Not delightful:Delightful	,978
Based on the above description, how would you describe the service you want to purchase? - Not fun:Fun	,976
Based on the above description, how would you describe the service you want to purchase? - Not thrilling:Thrilling	,975
Based on the above description, how would you describe the service you want to purchase? - Boring: Interesting	,970

Metodo di estrazione: Analisi dei componenti principali.

a. 1 componenti estratti.

A.B Expertise Scale

Test di KMO e Bartlett

Misura di Kaiser-Meyer-Olkin di adeguatezza del campionamento.		,920
Test della sfericità di Bartlett	Appross. Chi-quadrato	3455,869
	gl	10
	Sign.	,000

Comunalità

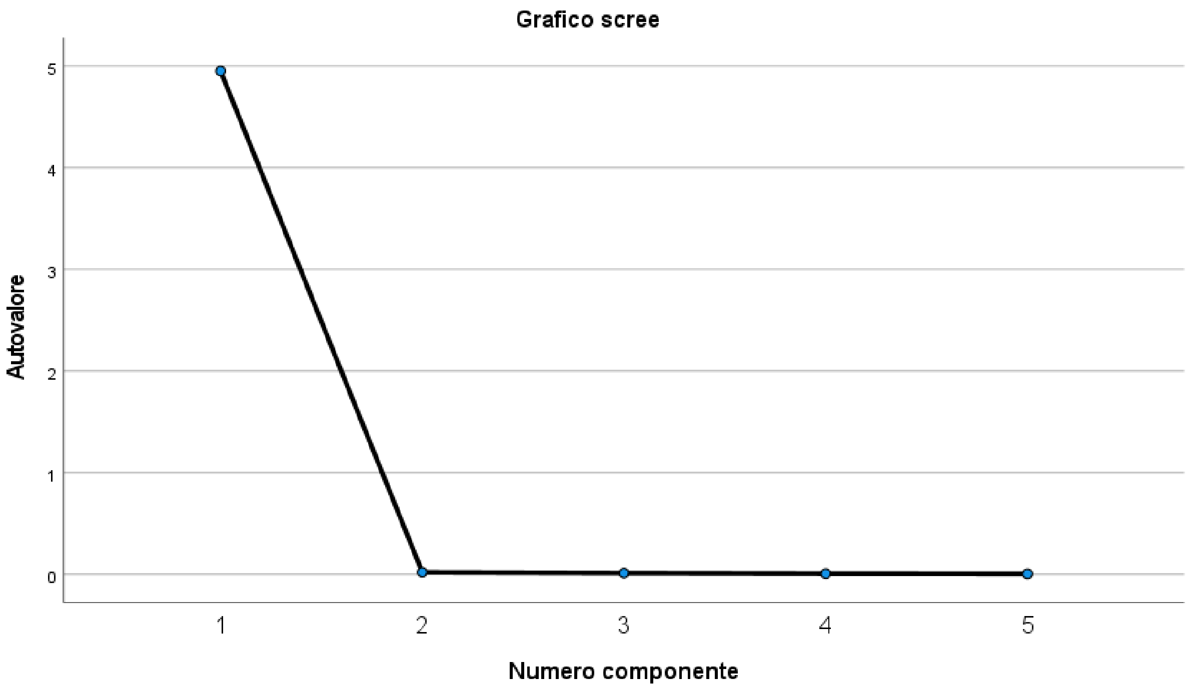
	Iniziale	Estrazione
Based on the situation you have just read about, how would you describe the Digital Human Avatar in charge of assisting you in purchasing the service? - Not an expert:Expert	1,000	,989
Based on the situation you have just read about, how would you describe the Digital Human Avatar in charge of assisting you in purchasing the service? - Inexperienced:Experienced	1,000	,985
Based on the situation you have just read about, how would you describe the Digital Human Avatar in charge of assisting you in purchasing the service? - Unknowledgeable: Knowledgeable	1,000	,993
Based on the situation you have just read about, how would you describe the Digital Human Avatar in charge of assisting you in purchasing the service? - Unqualified:Qualified	1,000	,992
Based on the situation you have just read about, how would you describe the Digital Human Avatar in charge of assisting you in purchasing the service? - Unskilled:Skilled	1,000	,992

Metodo di estrazione: Analisi dei componenti principali.

Varianza totale spiegata

Componente	Autovalori iniziali Totale	% di varianza	% cumulativa	Caricamenti somme dei quadrati di estrazione Totale	% di varianza	% cumulativa
1	4,951	99,017	99,017	4,951	99,017	99,017
2	,022	,436	99,453			
3	,013	,270	99,722			
4	,008	,159	99,882			
5	,006	,118	100,000			

Metodo di estrazione: Analisi dei componenti principali.



Matrice dei componenti[a]

	Componente 1
Based on the situation you have just read about, how would you describe the Digital Human Avatar in charge of assisting you in purchasing the service? - Not an expert:Expert	,994
Based on the situation you have just read about, how would you describe the Digital Human Avatar in charge of assisting you in purchasing the service? - Inexperienced:Experienced	,992
Based on the situation you have just read about, how would you describe the Digital Human Avatar in charge of assisting you in purchasing the service? - Unknowledgeable: Knowledgeable	,997
Based on the situation you have just read about, how would you describe the Digital Human Avatar in charge of assisting you in purchasing the service? - Unqualified:Qualified	,996
Based on the situation you have just read about, how would you describe the Digital Human Avatar in charge of assisting you in purchasing the service? - Unskilled:Skilled	,996

Metodo di estrazione: Analisi dei componenti principali.

a. 1 componenti estratti.

A.C Disclosure Willingness Scale

Test di KMO e Bartlett

Misura di Kaiser-Meyer-Olkin di adeguatezza del campionamento.		,766
Test della sfericità di Bartlett	Appross. Chi-quadrato	1373,771
	gl	3
	Sign.	<,001

Comunalità

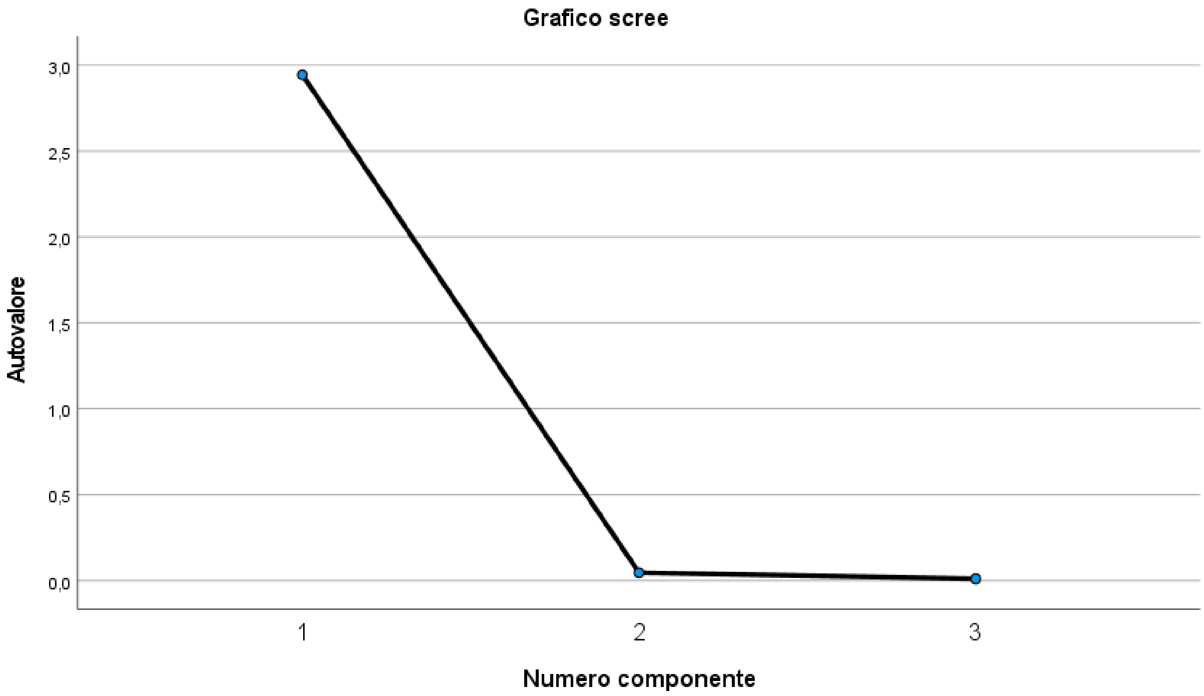
	Iniziale	Estrazione
Based on the same description, please indicate how much you agree with the following statements: - I am willing to provide my personal information when asked by this Digital Human Avatar	1,000	,987
Based on the same description, please indicate how much you agree with the following statements: - I am willing to disclose even sensitive personal information to this Digital Human Avatar	1,000	,969
Based on the same description, please indicate how much you agree with the following statements: - I am willing to be truthful in revealing my personal information to this Digital Human Avatar	1,000	,987

Metodo di estrazione: Analisi dei componenti principali.

Varianza totale spiegata

	Autovalori iniziali			Caricamenti somme dei quadrati di estrazione		
Componente	Totale	% di varianza	% cumulativa	Totale	% di varianza	% cumulativa
1	2,943	98,106	98,106	2,943	98,106	98,106
2	,046	1,539	99,644			
3	,011	,356	100,000			

Metodo di estrazione: Analisi dei componenti principali.



Matrice dei componenti[a]

	Componente 1
Based on the same description, please indicate how much you agree with the following statements: - I am willing to provide my personal information when asked by this Digital Human Avatar	,993
Based on the same description, please indicate how much you agree with the following statements: - I am willing to disclose even sensitive personal information to this Digital Human Avatar	,984
Based on the same description, please indicate how much you agree with the following statements: - I am willing to be truthful in revealing my personal information to this Digital Human Avatar	,994

Metodo di estrazione: Analisi dei componenti principali.

a. 1 componenti estratti.

F.B Reliability Test

B.A HED/UT Scale

Statistiche di affidabilità

Alpha di Cronbach	Alpha di Cronbach basata su elementi standardizzati	N. di elementi
,992	,993	10

Statistiche elemento-totale

	Media scala se viene eliminato l'elemento	Varianza scala se viene eliminato l'elemento	Correlazione elemento-totale corretta	Correlazione multipla quadratica	Alpha di Cronbach se viene eliminato l'elemento
Based on the above description, how would you describe the service you want to purchase? - Necessary:Unnecessary	32,42	449,273	,954	,948	,991
Based on the above description, how would you describe the service you want to purchase? - Effective:Ineffective	32,56	458,738	,949	,956	,991
Based on the above description, how would you describe the service you want to purchase? - Functional:Not functional	32,57	450,501	,966	,964	,991
Based on the above description, how would you describe the service you want to purchase? - Practical:Impractical	32,57	458,821	,952	,959	,991
Based on the above description, how would you describe the service you want to purchase? - Helpful:Unhelpuful	32,79	458,922	,951	,957	,991
Based on the above description, how would you describe the service you want to purchase? - Dull: Exciting	32,31	445,534	,971	,964	,991
Based on the above description, how would you describe the service you want to purchase? - Not delightful:Delightful	32,08	429,549	,975	,981	,991
Based on the above description, how would you describe the service you want to purchase? - Not fun:Fun	32,12	430,259	,974	,989	,991
Based on the above description, how would you describe the service you want to purchase? - Not thrilling:Thrilling	32,22	433,944	,971	,985	,991
Based on the above description, how would you describe the service you want to purchase? - Boring: Interesting	32,19	435,317	,966	,975	,991

B.B Expertise Scale

Statistiche di affidabilità

Alpha di Cronbach	Alpha di Cronbach basata su elementi standardizzati	N. di elementi
,997	,998	5

Statistiche elemento-totale

	Media scala se viene eliminato l'elemento	Varianza scala se viene eliminato l'elemento	Correlazione elemento-totale corretta	Correlazione multipla quadratica	Alpha di Cronbach se viene eliminato l'elemento
Based on the situation you have just read about, how would you describe the Digital Human Avatar in charge of assisting you in purchasing the service? - Not an expert:Expert	16,88	66,963	,991	,983	,997
Based on the situation you have just read about, how would you describe the Digital Human Avatar in charge of assisting you in purchasing the service? - Inexperienced:Experienced	16,90	67,976	,988	,978	,997
Based on the situation you have just read about, how would you describe the Digital Human Avatar in charge of assisting you in purchasing the service? - Unknowledgeable: Knowledgeable	16,81	66,710	,995	,990	,997
Based on the situation you have just read about, how would you describe the Digital Human Avatar in charge of assisting you in purchasing the service? - Unqualified:Qualified	16,81	66,616	,994	,991	,997
Based on the situation you have just read about, how would you describe the Digital Human Avatar in charge of assisting you in purchasing the service? - Unskilled:Skilled	16,82	66,367	,994	,991	,997

B.C Disclosure Willingness Scale

Statistiche di affidabilità

Alpha di Cronbach	Alpha di Cronbach basata su elementi standardizzati	N. di elementi
,990	,990	3

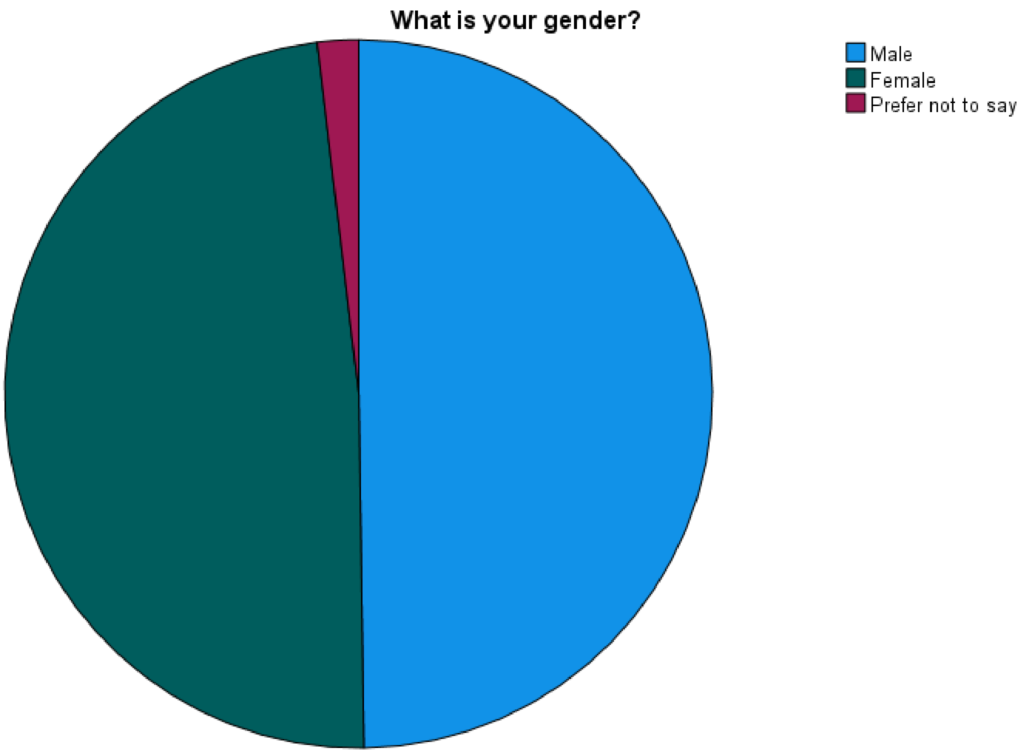
Statistiche elemento-totale

	Media scala se viene eliminato l'elemento	Varianza scala se viene eliminato l'elemento	Correlazione elemento-totale corretta	Correlazione multipla quadratica	Alpha di Cronbach se viene eliminato l'elemento
Based on the same description, please indicate how much you agree with the following statements: - I am willing to provide my personal information when asked by this Digital Human Avatar	8,23	15,284	,985	,980	,981
Based on the same description, please indicate how much you agree with the following statements: - I am willing to disclose even sensitive personal information to this Digital Human Avatar	8,52	15,704	,965	,932	,995
Based on the same description, please indicate how much you agree with the following statements: - I am willing to be truthful in revealing my personal information to this Digital Human Avatar	8,30	15,596	,986	,980	,981

C. Sample Structure

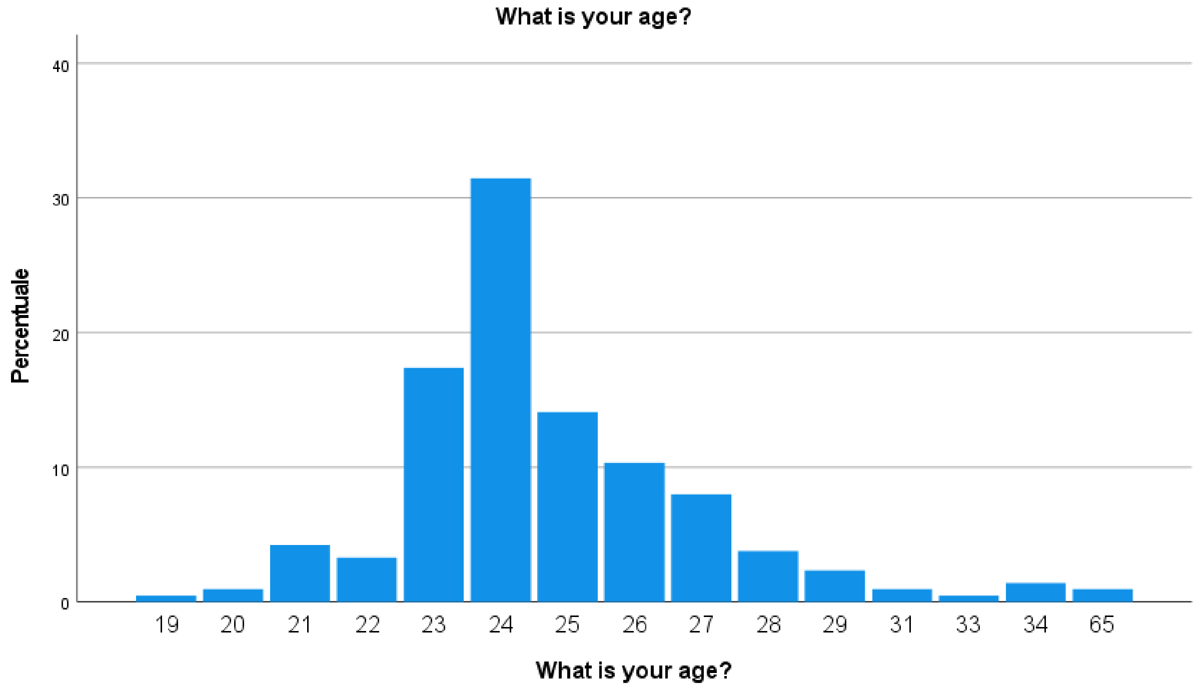
What is your gender?

		Frequenza	Percentuale	Percentuale valida	Percentuale cumulativa
Valido	Male	106	49,8	49,8	49,8
	Female	103	48,4	48,4	98,1
	Prefer not to say	4	1,9	1,9	100,0
	Totale	213	100,0	100,0	



What is your age?

		Frequenza	Percentuale	Percentuale valida	Percentuale cumulativa
Valido	19	1	,5	,5	,5
	20	2	,9	,9	1,4
	21	9	4,2	4,2	5,6
	22	7	3,3	3,3	8,9
	23	37	17,4	17,4	26,3
	24	67	31,5	31,5	57,7
	25	30	14,1	14,1	71,8
	26	22	10,3	10,3	82,2
	27	17	8,0	8,0	90,1
	28	8	3,8	3,8	93,9
	29	5	2,3	2,3	96,2
	31	2	,9	,9	97,2
	33	1	,5	,5	97,7
	34	3	1,4	1,4	99,1
	65	2	,9	,9	100,0
	Totale	213	100,0	100,0	



D. One-way ANOVA

Descrittive

DV

	N	Medio	Deviazione std.	Errore std.	95% di intervallo di confidenza per la media Limite inferiore	Limite superiore	Minimo	Massimo
,00	105	2,8032	1,40489	,13710	2,5313	3,0751	1,00	6,00
1,00	108	5,4198	1,47908	,14232	5,1376	5,7019	3,00	7,00
Totale	213	4,1299	1,94724	,13342	3,8669	4,3929	1,00	7,00

ANOVA

DV

	Somma dei quadrati	df	Media quadratica	F	Sig.
Tra gruppi	364,503	1	364,503	175,055	<,001
Entro i gruppi	439,348	211	2,082		
Totale	803,851	212			

E. Two-way ANOVA

Statistiche descrittive

Variabile dipendente: MED

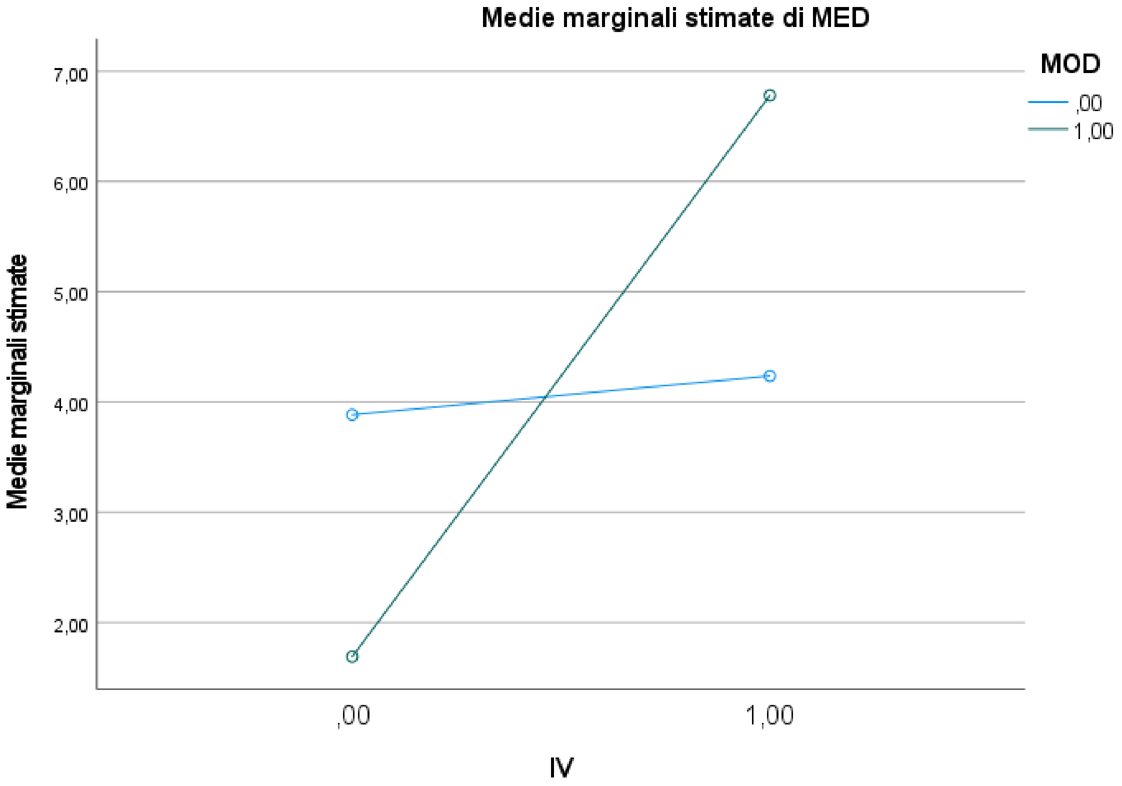
IV	MOD	Medio	Deviazione std.	N
,00	,00	3,8846	1,05856	52
	1,00	1,6906	,84541	53
	Totale	2,7771	1,45663	105
1,00	,00	4,2370	,96667	54
	1,00	6,7815	,49185	54
	Totale	5,5093	1,48875	108
Totale	,00	4,0642	1,02336	106
	1,00	4,2598	2,64792	107
	Totale	4,1624	2,00850	213

Test di effetti tra soggetti

Variabile dipendente: MED

Origine	Somma dei quadrati di tipo III	df	Media quadratica	F	Sig.
Modello corretto	698,559[a]	3	232,853	310,648	<,001
Intercetta	3664,713	1	3664,713	4889,079	<,001
IV	394,352	1	394,352	526,103	<,001
MOD	1,634	1	1,634	2,180	,141
IV * MOD	298,837	1	298,837	398,677	<,001
Errore	156,660	209	,750		
Totale	4545,640	213			
Totale corretto	855,220	212			

a. R-quadrato = ,817 (R-quadrato adattato = ,814)


Medie marginali stimate di MED
MOD
,00
1,00
Medie marginali stimate
7,00
6,00
5,00
4,00
3,00
2,00
,00
1,00
IV

F. Process Model 4

```
**************************************************************************
Model  : 4
    Y  : DV
    X  : IV
    M  : MED

Sample
Size:  213

**************************************************************************
OUTCOME VARIABLE:
 MED

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,6817      ,4647     2,1697   183,1570     1,0000   211,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     2,7771      ,1438    19,3192      ,0000     2,4938     3,0605
IV           2,7321      ,2019    13,5335      ,0000     2,3342     3,1301

**************************************************************************
OUTCOME VARIABLE:
 DV

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,9752      ,9510      ,1876  2037,5549     2,0000   210,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,2075      ,0703     2,9496      ,0035      ,0688      ,3461
IV            ,0629      ,0811      ,7758      ,4387     -,0970      ,2229
MED           ,9347      ,0202    46,1741      ,0000      ,8948      ,9746

****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,0629      ,0811      ,7758      ,4387     -,0970      ,2229

Indirect effect(s) of X on Y:
        Effect     BootSE   BootLLCI   BootULCI
MED     2,5536      ,1969     2,1782     2,9342

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000
```

G. Process Model 7

```
**************************************************************************
Model  : 7
    Y  : DV
    X  : IV
    M  : MED
    W  : MOD

Sample
Size:  213

**************************************************************************
OUTCOME VARIABLE:
 MED

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,9038      ,8168      ,7496   310,6483     3,0000   209,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant     3,8846      ,1201    32,3551      ,0000     3,6479     4,1213
IV            ,3524      ,1682     2,0951      ,0374      ,0208      ,6840
MOD         -2,1940      ,1690   -12,9833      ,0000    -2,5272    -1,8609
Int_1        4,7385      ,2373    19,9669      ,0000     4,2707     5,2063

Product terms key:
 Int_1    :        IV        x        MOD

Test(s) of highest order unconditional interaction(s):
       R2-chng          F        df1        df2          p
X*W      ,3494   398,6770     1,0000   209,0000      ,0000
----------
    Focal predict: IV        (X)
          Mod var: MOD       (W)

Conditional effects of the focal predictor at values of the moderator(s):

       MOD     Effect         se          t          p       LLCI       ULCI
     ,0000      ,3524      ,1682     2,0951      ,0374      ,0208      ,6840
    1,0000     5,0909      ,1674    30,4111      ,0000     4,7609     5,4209

**************************************************************************
OUTCOME VARIABLE:
 DV

Model Summary
          R       R-sq        MSE          F        df1        df2          p
      ,9752      ,9510      ,1876  2037,5549     2,0000   210,0000      ,0000

Model
              coeff         se          t          p       LLCI       ULCI
constant      ,2075      ,0703     2,9496      ,0035      ,0688      ,3461
IV            ,0629      ,0811      ,7758      ,4387     -,0970      ,2229
MED           ,9347      ,0202    46,1741      ,0000      ,8948      ,9746
```

```
****************** DIRECT AND INDIRECT EFFECTS OF X ON Y *****************

Direct effect of X on Y
     Effect         se          t          p       LLCI       ULCI
      ,0629      ,0811      ,7758      ,4387     -,0970      ,2229

Conditional indirect effects of X on Y:

INDIRECT EFFECT:
 IV          ->    MED         ->    DV

        MOD     Effect     BootSE   BootLLCI   BootULCI
      ,0000      ,3294      ,1812     -,0304      ,6863
     1,0000     4,7583      ,1927     4,3560     5,1040

Index of moderated mediation (difference between conditional indirect effects):
         Index     BootSE   BootLLCI   BootULCI
MOD     4,4289      ,2666     3,8856     4,9328
---

*********************** ANALYSIS NOTES AND ERRORS ************************

Level of confidence for all confidence intervals in output:
  95,0000

Number of bootstrap samples for percentile bootstrap confidence intervals:
  5000

------ END MATRIX -----
```

Summary

1. Introduction

1.1 Artificial Intelligence

Artificial intelligence (AI) is a term used to describe a system that employs technology to assess service scenarios in real time while using data gathered from digital and/or physical sources to provide alternatives, recommendations, suggestions, and tailored solutions to customer requests or problems, even those that are very complex (Xu et al., 2020).

Artificial intelligence (AI) is able to finish hundreds, thousands, or even millions of tasks very quickly and pick up new skills in whatever it is trained to do, and this is possible thanks to fundamental tools, such as machine learning and deep learning.

Nowadays, AI is used in a growing number of situations and technologies outside of only those related to computers. Some of these are smartphones, search engines, and customer service (Makridakis, 2017; Wirtz et al., 2018; Zhang et al., 2021). They also play a bigger and bigger part in fields like journalism (Carlson, 2015), the arts (Quackenbush, 2018), music production (Marshall, 2018), and marketing (Sterne, 2017), which were traditionally thought to require a high level of intellectual ability.

According to SAS and Gartner, every industry has a high demand for AI capabilities, including those for systems that may be used for automation, learning, legal aid, risk alerting, and research.

To give examples, AI applications can be used in the *healthcare* industry to read X-rays and give customized treatment; in *manufacturing*, AI can use recurring networks to assess factory IoT data from connected equipment to forecast predicted load and demand; in *life sciences*, the benefits include protecting the security of medications and accelerating the release of novel treatments; in *banking*, AI approaches can be applied to detect potentially fraudulent transactions, implement quick and precise credit rating, and automate routine data management chores; in the *public sector*, AI can improve the efficiency and effectiveness of programs, such as supporting national defence with mission readiness and predictive maintenance.

1.2 AI Recommendation Systems

A recommender system can be described as *"any system that produces individualized recommendations as output or has the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options"* (Burke, 2002; p. 331).

To tailor recommendations, many recommendation systems keep profiles of user activity (long- or short-term) or expressed preferences (Schafer et al., 2007), whereas other systems personalize results through conversational engagement (McGinty & Reilly, 2011).

Every recommender system needs one or more sources of knowledge to perform its task (e.g., *Social Knowledge*, *Individual Knowledge*, and *Content Knowledge*), and it is precisely based on the type of knowledge it uses that it is possible to classify these systems (Felfernig & Burke, 2008).

To produce a recommendation, AI recommendation systems mainly use content-based filtering and collaborative filtering (Namjun et al., 2019).
Content-based filtering evaluates a set of discrete properties when a user picks an article to produce a filter and recommends further articles that share the same characteristics (Pazzani, 1999). In contrast, Collaborative filtering builds a list of products in which a user would be interested in assessing a user's past activity, such as clicks, purchases, and assessments, combined with analogous decisions made by other users (Schafer et al., 2007).

1.3 The Anthropomorphization of AI

Anthropomorphism can be defined as the tendency to see the human in non-human forms and events (Guthrie Steward, 1995), and according to Epley et al. (2007), this tendency occurs when a non-human agent or inanimate object is given physical or non-physical traits, emotions, behavior, attributes, and human-like features.
In line with the tendency of humans to assign human-like features and feelings to lifeless or non-human objects from an early age (Derby, 1970; Lanier Jr. et al., 2013), consumer research and product marketing have found that anthropomorphism applied to product design results in higher levels of sympathy in humans (Aggarwal & McGill, 2007; Landwehr et al., 2011; Wen Wan et al., 2017). For this reason, hardware and software engineers attempt to incorporate human characteristics and features into technology to help people interact with the system and grow familiar with its capabilities (Burgoon et al., 2000; Epley et al., 2007).
To give an example, Landwehr et al. (2011) found that by designing the design in a way that recalls human features, consumers are more likely to anthropomorphize, potentially leading to greater product appreciation. Through anthropomorphization, interactions between humans and an inanimate object can similarly become human-human interactions, leading to attachment to the object and the satisfaction of a person's requirements for comfort, likeability, identity, and self-efficacy (Wan & Chen, 2021).
Inanimate objects that are seen by humans as having an anthropomorphic quality include computers (Nass et al., 1996), but also information technology and information systems (Pfeuffer, Benlian, Gimpel, & Hinz, 2019).
Historically, artificial intelligence has been viewed as being anthropomorphic. In fact, some of its algorithms employ biomimetic designs in an intentional effort to achieve a kind of digital isomorphism of the human brain, while others make use of more general learning techniques that are consistent with well-liked theories of cognitive science and social epistemology (Watson, 2019).
The ability of AI to mimic human cognitive processes and interactions offers anthropomorphic clues that drive users to regard them as similar to people and develop emotional attachments (Wan & Chen, 2021) and this also leads to a change in our perceptions of technology and its use (Kim & Im, 2023).
Given the ongoing development of AI and its intelligence levels, it is assumed that its capabilities, emotional and social skills, and its degree of humanization will increase even more (Hermann, 2022).

Applications of AI, such as chatbots, service robots, and intelligent personal/digital assistants (like Siri or Alexa), already have human morphology, names, and characteristics, such as the ability to recognize language and emotions (Huang & Rust, 2021; Ramadan et al., 2021; Wan & Chen, 2021).

1.4 Avatars

Avatars are virtual characters that can be understood as anthropomorphic-looking digital beings that can interact and are controlled by a person or software as a result of advancements in computer technology (Miao et al., 2022).

Regarding the entity of control over the avatar, either a human operator or an automated computer program could be involved (Nowak & Fox, 2018). According to some, when control is entrusted to technology one speaks of an agent or bot, while when control is entrusted to humans one speaks of an avatar (Nowak & Fox, 2018). However, due to financial constraints, in current business practices, artificial intelligence seems to be the primary enabler of digital avatars.

To help academics and managers with the identification of the components that make an avatar more or less useful for achieving particular objectives, Miao et al. (2022) created a 2 x 2 taxonomy to categorize avatars taking into consideration two fundamental variables: form realism (how closely an avatar resembles a human being) and behavioral realism (how closely the avatar behaves like a human in the physical world) (Bailenson et al., 2008; Blascovich et al., 2002; Fox et al., 2015).

Using this 2 x 2 taxonomy, the authors identified four distinct types of avatars:

- *Simplistic*: a simplistic avatar has minimal intellect (e.g., scripted, task-specific communication only) and an unrealistic human appearance (e.g., a 2D, visually static, cartoonish image) which would seem to be most useful for offering simple, hassle-free solutions for quickly doing specified duties (like selling high-quality products and answering inquiries), especially when the risk is low (as with affordable online shopping).

- *Superficial:* a superficial avatar has a realistic anthropomorphic look (e.g., 3D, visually dynamic, photorealistic image), but limited behavioral realism, in that it can only respond to queries with pre-programmed responses.

- *Intelligent Unrealistic Avatar*: an intelligent unrealistic avatar displays a non-realistic (for example, cartoonish) human appearance but possesses human-like cognitive and emotional intelligence. They appear to be especially useful for complex relational transactions involving private information (such as finances or health), as they can engender a feeling of non-judgment.

- *Digital Human Avatar*: a digital human avatar is the most sophisticated type of avatar, distinguished by an extremely realistic anthropomorphic form and human-like emotional and cognitive abilities, which seem to work best in situations that involve a lot of complexity or risk (like financial investments) or a high degree of personalization.

1.5 Relevance

1.5.1 Academic Relevance

Nicolas Pfeuffer et al. (2019) pointed out that anthropomorphic information systems, such as conversational agents, offer users a better experience and greater satisfaction with services if designed thoughtfully. In this sense, they believe there is a need to research the impact of anthropomorphic characteristics of information systems to assess their effects and create fresh design techniques that can be used as rules of thumb.

Among the anthropomorphic characteristics to which future research should pay particular attention is the sexual gender of AI, to investigate how gender biases are also effectively applied to artificial intelligence systems (Alabed, Javornik & Gregory-Smith, 2022; Diederich et al., 2022; West et al., 2019).

This phenomenon of study is especially relevant considering the current prevalence of AI agents with female characteristics (e.g., voice, name), which has also been alarmingly highlighted by UNESCO, for whom this prevalence risks reinforcing gender stereotypes (West et al., 2019).

A recent study that investigated this phenomenon is attributed to Jungyong Ahn, Jungwon Kim, and Yongjun Sung (2022), who investigated the effects of gender stereotypes on the evaluation of AI recommendations for hedonic and utilitarian products. Anyways, the authors of this study stated that further research is needed to generalize these results, considering not only products but also services (Pizzi et al., 2021), which this study will focus on.

In addition, unlike the aforementioned study that investigated gender stereotypes' impact on poorly anthropomorphized chatbots, this research will consider a more advanced and highly anthropomorphized type of artificial intelligence, namely the Digital Human Avatar, which is particularly useful when customers require a personalized recommendation (Miao et al., 2022).

1.5.2 Managerial Relevance

The Marketing Science Institute (2020) has placed artificial intelligence as a priority in research for 2020-2022 because it is seen as an important technology that can significantly impact marketing management capabilities, strategies, function optimization, and accountability. In line with what has just been reported, a study conducted by McKinsey & Co. on more than 400 AI use cases in 19 industries and 9 business functions, showed that marketing and sales domains hold the greatest potential value for artificial intelligence (Chui et al., 2018). According to Columbus (2019), marketers intend to leverage AI in areas including segmentation and analytics (in relation to marketing strategy) as well as messaging, personalization, and predictive behaviors (in relation to consumer behaviors).

Despite the great potential of AI, consumers still have reservations about it, which is a potential barrier to its adoption (DataRobot, 2022) and, in line with what has just been said, according to research (Castelo et al.,

2018; Gray, 2017), customers are less likely to employ AI for jobs involving subjectivity, intuition, and affect because they believe it lacks affectivity or empathy (Luo et al., 2019) needed to perform such tasks and relatively less able to identify the particularities of each customer (Longoni et al., 2019).
A method that is used to stimulate customer empathy toward AI is anthropomorphization, and a confirmation of this is the increasing use of avatars in contemporary marketing strategies. The use of avatars is anticipated to rise by 187 percent for consumer products and 241 percent for the travel and hospitality sectors, as businesses spend extensively on them to better interact with and serve their customers (Sweezey, 2019). According to Torresin (2019), 87 percent of banking organizations either already employ avatars or have plans to do so within the next two years. In the case of digital human avatars, which this study focuses on, the estimated value of the global market in 2020 was $10.03 billion and this value is expected to reach $527.58 billion in 2030 (Emergen Research, 2023).
Digital human avatars have become especially popular since the introduction of the Metaverse, or the new 3D digital environment that allows users to enjoy authentic online personal and professional experiences through the use of virtual reality, augmented reality, and other cutting-edge Internet and semiconductor technologies (McKinsey, 2022). The interest in the metaverse is not only from consumers and, as a matter of fact, private capital is betting heavily on it: more than $120 billion flowed from the metaverse in 2022, and McKinsey (2022) estimates that by 2030, the metaverse might provide up to $5 trillion in value. By 2026, 25 percent of individuals will spend at least one hour per day engaging in activities such as work, study, socializing, entertainment, and/or shopping in the metaverse, predicts Gartner, Inc. (2022).
This virtual world is set to impact every business that interacts with consumers daily, and for that reason, forecasts estimate that 30 percent of organizations worldwide will have metaverse-ready products and services by 2026 (Gartner, 2022)

2. Theoretical Framework

A theoretical summary of the current work will be given in this chapter. The primary study variables—Service Type, Expertise, Disclosure Willingness, and Avatar Gender—as well as their interactions, will be covered to establish the research hypotheses that will be investigated later in the thesis.

2.1 Service Type

A service is "*any act or performance that one party can offer to another, which is essentially intangible and does not result in the ownership of anything*" (Philip Kotler, 2012, p. 356).
In light of the substantial diversity that exists within the service domain, Voss et al. (2016) make an argument for the significance of identifying the primary context within which firms operate and engage with their customers. Very useful in this regard is Higgins' (1998) Normative Orientation Theory, which is traditionally invoked to describe and distinguish between hedonic and utilitarian products.
Despite the fact that consumption entails both hedonistic and practical concerns, consumers generally tend to regard what they consume as predominantly hedonic or utilitarian (Khan, Dhar & Wertenbroch, 2005). Hedonic consumption is predominantly affective, based on sensory enjoyment, and it is measured by how

satisfying a product is on an individual basis. Contrarily, utilitarian consumption is more cognitive, centered on functional objectives, and measured by how much a product serves as a tool to achieve a goal (Crowley, Spangenberg & Hughes, 1992; Holbrook, 1994; Botti & McGill, 2011).

Regarding the differences that exist between hedonic and utilitarian services, some studies have investigated the influence that the type of service has on the effectiveness of the different marketing appeals used to promote them (Zhang et al., 2014), the effectiveness of the type of spokesperson used (Stafford, Stafford M. R., & Day, 2002) but also the influence that individual consumer characteristics have on the perceived quality and fulfillment of hedonic and utilitarian services, like for example the impact that happiness has on service evaluation and engagement (Hellén & Sääksjärvi, 2011).

2.2 Disclosure Willingness

Self-disclosure (Collins & Miller, 1994) has been defined as "*any information about oneself that a person verbally communicates to another person*" (Cozby, 1973; Wheeless, 1976) and it is a topic that has been extensively explored given the growing number of businesses, both online and off, that are attempting to gather personal information from their customers or visitors in order to use it for various analytical and/or communication objectives (Schofield & Joinson, 2008).

The motivations behind the behavior of disclosing personal information have been investigated from different theoretical perspectives. According to Social Exchange Theory (Thibaut & Kelley, 1959; Homans, 1961; Emerson, 1976), people consider the interpersonal costs and rewards of a social action before deciding whether or not to engage in it.

The Privacy Calculus Theory (Culnan & Armstrong, 1999), which examines the factors that encourage or dissuade customers to share information online, has typically served as the foundation for current research in this area. This idea holds that while selecting whether to release personal information, people must weigh the expected advantages against the risks of privacy loss (Robinson, 2017; Smith et al., 2011).

In exchange for a chunk of their privacy, people expect to get customized offers from released data (Montecchi & Plangger, 2020), in line with the previously mentioned Social Exchange Theory (Emerson, 1976; Homans, 1961; Thibaut & Kelley, 1959).

A study conducted by Fernandes and Pereira (2021) on the motivations behind the disclosure of personal data online in transactional contexts (i.e., associated with commercial contexts including online banking, e-commerce, online travel websites, streaming services, and e-health services branded mobile apps) found that utilitarian benefits (e.g., utility and convenience) are more important determinants of data disclosure than hedonic benefits.

In light of what has just been reported, the following hypothesis has been formulated:

H1: The Utilitarian service type has a more positive impact on the disclosure willingness compared to the hedonic one.

2.3 The Mediating Role of Expertise

Hovland et al. (1953) identified "expertise" as *"the extent to which a communicator is perceived to be a source of valid assertions"* (p. 21).

In accordance with the Traditional Source Credibility Model (Hovland, Janis, & Kelley, 1953; Hovland & Weiss, 1951; Johansson & Sparredal, 2002; Ohanian, 1990) and the Source Attractiveness Model (Johansson & Sparredal, 2002; McGuire, 1968, 1985), qualities like expertise, trustworthiness, and attractiveness have been measured as positive features that significantly provoke receivers' positive attitude and even purchasing (Applbaum & Anatol, 1972; Hovland et al., 1953).

According to previous research on source expertise in persuasion (Horai, Naccari & Fatoullah, 1974; Maddux & Rogers, 1980; Mills & Harvey, 1972; Ross, 1973), the source's perceived expertise has a favorable effect on attitude change. In line with the latter statement, a higher subjective perception of competence seems to be associated with an increased trust in and positive attitude toward AI (Pitardi & Marriott, 2021).

As pointed out by Longoni and Cian (2022), people believe that artificial intelligence advisors are more (less) competent in assessing the utilitarian (hedonic) value of attributes and generating utilitarian-oriented (hedonic) recommendations than human advisors. This is because humans are thought to possess emotions and experiential skills, whilst AI, robots, and computers are thought to possess reason and logic. Thus, the preference of human (AI) over AI (human) recommendations in the case of hedonic (utilitarian) consumption depends on the fact that hedonic value assessment is based on experiential, emotional, and sensory criteria whereas utilitarian value assessment is based on factual, rational and logical evaluation criteria (Longoni & Cian, 2022).

The connection between perceived AI competence and utilitarian contexts is further supported by a study by Belanche, Casaló, Schepers, and Flavián (2021), who discovered that perceived robot competence primarily affects consumers' utilitarian expectations (i.e., functional and monetary value) and, in line with what has just been reported, according to research done by Liu, Yi, and Wan (2022), consumers are more willing to use a service robot viewed as competent in utilitarian service contexts.

Drawing upon past research, it can therefore be said that consumers prefer to base their purchasing behavior on AI recommendations over human recommendations when consumption is predominantly utilitarian, whereas when consumption is predominantly hedonic, human recommendations are preferred over AI recommendations.

Formally:

H2: The perceived Avatar expertise mediates the relationship between the service type and the disclosure willingness. The Utilitarian service type (vs Hedonic service type) increases the perceived Avatar expertise by users.

The relevance of expertise for the adoption of AI can also be linked to the willingness of users to share their data, which is the basis for the efficient and personalized performance that artificial intelligence can offer us.

This connection between expertise, also called competence (Whitehead, 1968), and the willingness to provide personal data was investigated by a study conducted in 2022 by Miriam Gieselmann and Kai Sassenberg. These two authors found that users are open to sharing personal information in exchange for the intellectual capabilities of AI, and meta-cognitive heuristics only minimally enhance privacy issues while remaining unaffected by user openness to sharing information. In line with this study, Pizzi et al. (2023) discovered that when a chatbot is perceived as competent, people are less skeptical about the technology—but only when they think they are capable of accurately discerning others' ultimate intentions.
Considering what was said above, the following hypothesis has been stated:

H3: The perceived Avatar expertise mediates the relationship between the service type and the disclosure willingness. A higher perceived Avatar expertise leads to a higher disclosure willingness.

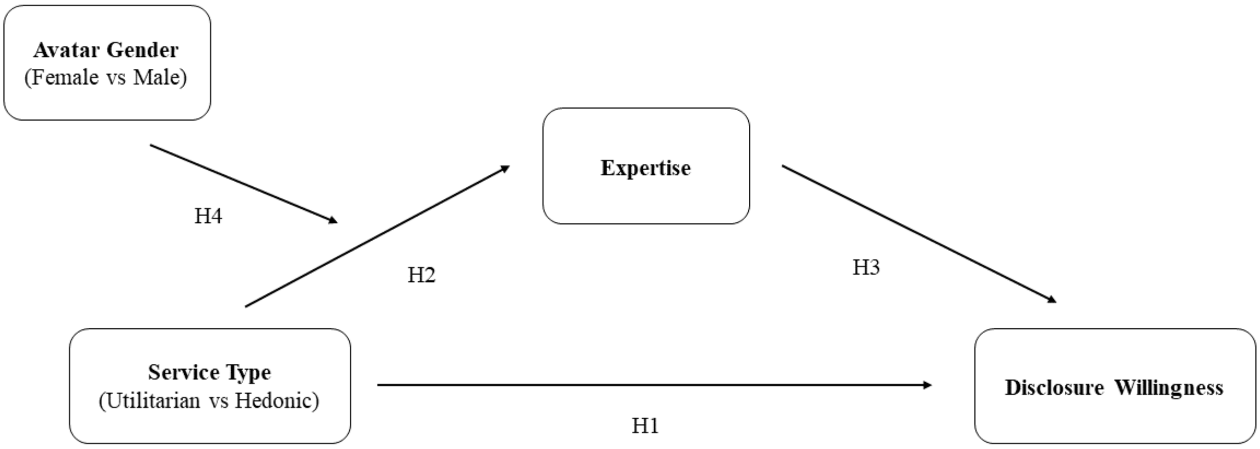
2.4 The Moderating Role of Avatar Gender

Customers typically trust humans and avoid autonomous technology, according to Baccarella et al. (2021), since artificially intelligent systems are thought to be less capable of giving trustworthy, competent, and relevant information. This is because customers view automated systems as being less adaptable and flexible, particularly in conditions defined by significant uncertainty (Leo & Huh, 2020) or circumstances that call for an explanation, such as when a poor service outcome occurs (Huang & Qian, 2021).
To reduce consumer resistance, artificial intelligence (AI) agents with anthropomorphic designs are becoming more and more common, with significant advances occurring particularly in the hospitality sector (Fan et al., 2020; Lu et al., 2019; Yu, 2020). According to De Visser et al. (2017), designers think that highly anthropomorphic AI service agents can increase the willingness of users to employ them, hence boosting commercial success.
Most AI service agents are created with human qualities, encompassing both psychological (language style, emotions, etc.) and non-psychological (appearance, gestures, etc.) characteristics.
Anthropomorphic characteristics, such as physical appearance (Eyssel & Hegel, 2012) and voice (Powers et al., 2005; Siegel et al., 2009), can also influence how the biological gender of an Information System (IS) is perceived, which in turn triggers behaviors, cultural norms, and psychological characteristics that are typically associated with men or women (Pfeuffer et al., 2019).
Eyssel and Hegel (2012) showed in their study that the sexual gender of robots, made explicit by aesthetic clues such as haircuts, activates gender stereotypes that influence the type of tasks (male vs. female) perceived as more suitable for robots (male vs. female).
Shifting the focus from robots to chatbots, Fox and Nowak (2018) argue that when anthropomorphic chatbots (e.g., avatars) present a certain sexual gender, gender stereotypes are activated that lead people to expect them to have gendered knowledge, influenced by the general stereotyping of men and women.
Similarly, a study by Ernst and Herm-Stapelberg (2020) found that people perceive virtual assistants (e.g., Siri) with a male voice as more competent than those with a female voice.

According to a number of studies, stereotyping is more likely to happen when technology is applied in areas that are specific to either gender rather than in areas that are gender-neutral. As a result, when a woman is represented by technology, people judge her to be more competent in fields that are more common for women than in technical or other fields that are seen to be more male-centric, and the opposite is also true. The link between sexual gender and higher levels of perceived competence is based on gender stereotypes whereby women are expected to be warm, helpful towards others, and caring, while for men, the expectations are related to their agency, competence, and authority (Ellemers, 2018).
Since hedonic consumption is predominantly affective and based on sensory enjoyment, while utilitarian consumption is more cognitive and centered on functional objectives, (Crowley, Spangenberg & Hughes, 1992; Holbrook, 1994; Botti & McGill, 2011), it is expected that female (vs. male) AI is perceived as more competent when the recommendation is related to a hedonic (vs. utilitarian) service and vice versa.
Putting this formally:

H4: The Avatar Gender moderates the relationship between service type and perceived Avatar expertise. In particular, the female gender related to a hedonic service leads to a higher perceived Avatar expertise, whereas the male gender related to a utilitarian service leads to a higher perceived Avatar expertise.

Taking into account the relationships mentioned above, the following conceptual model has been created:



3. Experimental Research

3.1 Experiment Overview

The primary objective of this study is to investigate the effect that the sexual gender of digital human avatars (female vs. male) has on consumers' perceived level of competence in making highly personalized recommendations for different types of services (hedonic vs. utilitarian), which is also hypothesized to have an impact on consumers' willingness to provide their data to receive such recommendations.

To validate the stimuli used in the main study, namely the Service Type (hedonic vs. utilitarian) and Avatar Gender (female vs. male), a pre-test was initially conducted.
Once the pre-test was carried out and it was ascertained that the stimuli were perceived correctly by the respondents, it was possible to proceed with the next step.
The main study used a 2 (Service Type: hedonic vs. utilitarian) x 2 (Avatar Gender: female vs. male) between-subjects design, in which each respondent was exposed to only one condition in a randomized manner, whereby the chance of being exposed to any treatment was the same for each participant. In this way, carry-over effects were avoided whereby respondents, if exposed to more than one condition, can use what was learned from one condition in the next (Charness et al., 2012).
SPSS software (Statistical Package for Social Science) was used to assess the significance of the hypotheses. Specifically, a One-way ANOVA was used to validate H1, while Model Process 4 was used to validate H2 and H3. To validate H4, we used Process Model 7.

3.2 Pretest Design

The pretest consists of a questionnaire, constructed using Qualtrics XM, divided into four parts (see Appendix C). The initial part consists of an informative introduction for respondents, in which an explanation of the academic purpose of the study is given and full compliance with privacy regulations regarding data collection and management is ensured.
Then, after brief instructions on how to correctly complete the questionnaire, the second part of the survey consisted of a randomized block consisting of two separate scenarios (sourced from the paper *"An emerging theory of avatar marketing*", Miao et al., 2022) regarding the sexual gender of the Digital Human Avatar (female vs. male), followed by a 7-point Likert scale that required candidates to express their perception of the image across three items (female, male, neutral) that was already used in a study conducted by Perugia et al. (2023) and aimed at investigating the perceived age and sexual gender of the humanoid robots in the ABOT dataset. The third part of the pretest is instead aimed at assessing the perception of the type of service and consists of a randomized block consisting of two distinct scenarios concerning the type of service perceived (hedonic vs. utilitarian), followed by the HED/UT differentiated semantic scale.
The texts concerning services were formulated independently, where the choice of utilitarian service is due to the work *"The emotional influence on satisfaction and complaint behavior in hedonic and utilitarian services"* (Calvo-Porral & Otero-Prada, 2021) while the choice of hedonic service is due to two studies: *"Hedonic service consumption and its dynamic effects on sales in the brick-and-mortar retail context"* (Zhou et al, 2023) *and "Verifying the hedonic vs. utilitarian consumer attitudes categorization: the case of spas and salons"* (Hanks & Mattila, 2012).
As for the scale used, it is derived from the work *"Measuring the hedonic and utilitarian dimensions of consumer attitude"* (Voss, Spangenberg, & Grohmann, 2003).
The final part of the pretest consists of four socio-demographic questions to find out the characteristics that distinguish the sample, namely age, gender, level of education, and occupation.

Once the data had been collected, they were analyzed with the help of the statistical software SPSS (Statistical Package for Social Science).

3.3 Design

The questionnaire consists of six parts, the first three of which represent the pre-test that was previously conducted to test the manipulation of the Avatar Gender and Service Type.

The fourth part of the survey was represented by a further randomized block consisting of four separate scenarios composed of the combination of the two categorical variables (Avatar Gender and Service Type). In fact, the randomization process was essential within the structure of the questionnaire to obtain a uniform number of exposures to all visual stimuli.

To avoid potential cognitive bias and brand sentiment, all scenarios are represented by mock-ups of service descriptions and Digital Human Avatars.

The fifth part of the survey was introduced to the respondents after being subjected to the observation of one of the four scenarios and this block consists of two prevalidated scales: the first scale for the mediator, which stems from the paper "*Construction and Validation of a Scale to Measure Celebrity Endorsers' Perceived Expertise, Trustworthiness, and Attractiveness*" (Ohanian, 1990) and the second scale for the dependent variable, which comes from the paper "*Self-Disclosure and Liking: A Meta-Analytic Review*" (Collins & Miller, 1994) and later taken up by Cho (2006) in his study "*The Mechanism of Trust and Distrust Formation and Their Relational Outcomes*".

Finally, the sixth and last part of the questionnaire is characterized by the block dedicated to socio-demographic questions, in which respondents were asked about their age, gender, level of education, and occupation.

3.4 Experimental Results

The data collected through the survey questionnaire generated on Qualtrics XM were exported to the statistical software SPSS (Statistical Package for Social Science) for analysis.

After conducting both factor analysis and reliability tests, along with the manipulation check relative to the pre-test, the main hypotheses of the conceptual research model were analyzed to confirm or reject its statistical significance and thus its relative success.

To test the significance of the conceptual model's direct hypothesis (H1), a comparison of averages was conducted by applying a One-way ANOVA (see Appendix F.D) as an analysis to test the effect of the independent variable (Service Type) against the dependent variable (Disclosure Willingness).

Since the average value (2.8032) recorded by the group of respondents subjected to the hedonic scenario (coded with 0) is lower than the average (5.4198) value recorded by those exposed to the utilitarian scenario (coded with 1), and the p-value recorded (0.001) is statistically significant ($p\text{-value} < \alpha = 0.05$), it is possible to say that the utilitarian service type has a more positive impact on the disclosure willingness compared to the hedonic one, confirming H1.

To test the significance of the moderating hypothesis of the conceptual model, a comparison between averages was conducted by applying a Two-way ANOVA (see Appendix F.E) to test the joint effect of the independent variable (Service Type) and the moderating variable (Avatar Gender) against the mediating variable (Expertise). It was possible to note that the group of respondents (52 people) subjected to the scenario coded with 0,0 (hedonic; female) recorded a mean value of 3.8846, the subjects (53 people) subjected to the visual condition coded with 0,1 (hedonic; male) recorded a mean value of 1. 6906, the group of respondents (54 people) subjected to the visual condition coded with 1,0 (utilitarian; female) showed a mean value of 4.2370 while the subjects (54 people) subjected to the visual condition coded with 1,1 (utilitarian; male) showed a mean value of 6.7815. Furthermore, thanks to the p-value view made possible by the between-subjects effects test table, it was possible to confirm the success of the interaction effect postulated by H4, as can be seen from the Interaction Plot in which a disordinal interaction with crossover is shown.

To test the significance of the indirect hypotheses of the conceptual model, a regression analysis was conducted by applying the Process Macro Version 4.0 model 4 developed by Andrew F. Hayes, so as to test the direct and mediating effect (see Appendix F.F).

Regarding the direct effect between X and Y (H1), through observation of the SPSS output, it was possible to observe a p-value equal to 0.4387, an adverse confidence interval (LLCI= -0.0970; ULCI= 0.2229) and a positive regression coefficient β equal to 0.0629. Therefore, this effect was not statistically significant, not confirming H1 (main effect).

With regard to the first section of the indirect effect between X and M (H2), through the examination of the SPSS results, a p-value of 0.0000, a favorable confidence interval (LLCI=0.3342; ULCI=3.1301) and a positive regression coefficient β of 2.7321 were observed. Therefore, this effect was statistically significant, confirming H2 (the first part of the indirect effect). Moving on to the second section of the indirect effect between M and Y (H3), through the observation of the SPSS output, it was possible to observe a p-value equal to 0.0000, a favorable confidence interval (LLCI=0.8948; ULCI=0.9746) and a positive regression coefficient β equal to 0.9347. Therefore, this effect was statistically significant, confirming H3 (the second part of the indirect effect).

Considering the results, as both sections of the indirect effect were statistically significant, whereas the direct effect was not, it was possible to confirm the success at the global level of the mediation effect (indirect effect), finding full mediation.

In order to test the significance of all hypotheses of the conceptual model, a regression analysis was conducted by applying the Process Macro Version 4.0 model 7 developed by Andrew F. Hayes, so as to test the direct, mediating, and moderating effect of the research (see Appendix F.G).

Regarding the direct effect between X and Y (H1), through observation of the SPSS output, it was possible to observe a p-value equal to 0.4387, an adverse confidence interval (LLCI= -0.0970; ULCI= 0.2229) and a positive regression coefficient β equal to 0.0629. Therefore, this effect was not statistically significant, not confirming H1 (main effect).

With regard to the first section of the indirect effect between X and M (H2), through the examination of the SPSS results, it was possible to observe a p-value equal to 0.0374, a favorable confidence interval (LLCI=0.0208; ULCI=0.6840) and a positive regression coefficient β equal to 0.3524. Therefore, this effect was statistically significant, confirming H2 (the first part of the indirect effect).

Moving on to the second section of the indirect effect between M and Y (H3), through the observation of the SPSS output, it was possible to observe a p-value equal to 0.0000, a favorable confidence interval (LLCI=0.8948; ULCI=0.9746) and a positive regression coefficient β equal to 0.9347. Therefore, this effect was statistically significant, confirming H3 (the second part of the indirect effect).

Finally, regarding the interaction effect between X and W with respect to M (H4), through the observation of the SPSS output, it was possible to observe a p-value equal to 0.0000, a favorable confidence interval (LLCI=4.2707; ULCI=5.2063) and a positive regression coefficient β equal to 4.7385. Therefore, this effect was also statistically significant, confirming H4 (interaction effect).

Thanks to the success of this double check carried out by means of Model 7, a full mediation (a phenomenon that occurs when the two sections of the indirect effect are statistically significant regardless of the direct effect between X and Y) and a significant interaction effect were demonstrated.

3.5 Implications, Limitations, and Future Research

From a theoretical point of view, this study set out to address the need to pay more attention to the effects of sexual gender attribution on artificial intelligence that has been raised by several scholars (Alabed, Javornik & Gregory-Smith, 2022; Diederich et al., 2022; West et al., 2019).

This goal was also recently pursued by Jungyong Ahn, Jungwon Kim, and Yongjun Sung (2022), who investigated the effects that gender stereotypes, the outcome of assigning a sexual gender to chatbots, have on consumers' evaluations of recommendations for utilitarian and hedonic products. The aforementioned authors, together with Pizzi et al. (2021), however, emphasized the importance of focusing not only on products but also on services, which is why this thesis considered utilitarian and hedonic services.

This study showed that male Avatars are perceived to be more competent for utilitarian service recommendations while female Avatars are perceived to be more competent for hedonic services and this evidence confirms what other scholars have already found in the past, i.e. that the attribution of a sexual gender to forms of technology such as robots (Eyssel & Hegel, 2012) or chatbots (Fox & Nowak, 2018) results in the activation of gender stereotypes in consumers, which leads them to expect from these technological forms skills differentiated according to the particular sexual gender that has been attributed to them (e. g. Bastiansen, Kroon, & Araujo, 2022; Nass & Moon, 2000), as gender stereotypes are based on the assumption that men and women have different skills.

The perceived expertise of the Avatar is very important for the purposes of the recommendation as this study found that a higher perception of expertise (influenced by both the type of service and the moderating effect played by the Avatar's sexual gender) leads to a higher propensity of consumers to disclose their information, thus confirming the relationship between expertise and disclosure willingness previously found by other authors in their studies (Gieselmann & Sassenberg, 2022; Pizzi et al., 2023). The willingness to disclose one's data is functional for recommendation purposes since it is because of the data provided by users that recommendation systems can formulate personalized recommendations and this willingness to disclose was found to be influenced both by the perceived expertise of the avatar and by the type of service to be recommended, confirming what other authors have found in the past (Culman & Amstrong, 1999; Kraft et al., 2017; Robinson, 2017; Smith et al., 2011).

As far as practical implications are concerned, this study differs from the one conducted in 2022 by Jungyong Ahn, Jungwon Kim, and Yongjun Sung not only for focusing on services and not goods but also for taking as the object of study not chatbots but a form of technology powered by highly anthropomorphized artificial intelligence, the Digital Human Avatars. In fact, the major managerial contribution of this study was to investigate the factors that contribute to influencing the effectiveness of this recent form of technology that, considering the future relevance of virtual realities such as the Metaverse, is set to flourish in the coming years (Emergen Research, 2023).

By demonstrating that the sexual gender attributed to the Digital Human Avatar influences the degree to which it is perceived to be competent according to the type of service to be recommended, this study offers marketers who want to make use of this highly anthropomorphized form of technology a cue on the basis of which they can better adapt the anthropomorphic design of the Avatar to the expectations of consumers according to the type of service they offer, in order to improve its effectiveness.

However, due to budget limitations and the impossibility of using a suitable structure to subject the respondents to different types of stimuli, this study could not show the sample members a Digital Human Avatar at its full potential. Digital Human Avatars present an astonishing intelligence both cognitively and emotionally, which is why they can communicate with humans through both verbal and non-verbal communication but, as the right tools were not available, it was not possible to show the respondents of the questionnaire an avatar in 3D form, nor was it possible to create a form of interaction between them.

The highly anthropomorphized appearance was communicated to the respondents visually with the help of an image, while their intellectual potential was reported to the subjects by means of a brief description above the avatar image.

However, in light of the relevance that these avatars may have for companies in virtual realities such as the Metaverse, it is good that future studies that have the necessary means try to investigate the effects of the human characteristics attributed to these avatars, such as sexual gender, age or race, by providing the right context, i.e. within these virtual realities in which these avatars would then be used. This would expose consumers to a Digital Human Avatar to the fullest extent of its capabilities and provide contextualized results.