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# Trust in the Digital Age: Perceived Risk as a Mediator between e-WOM, ChatGPT Recommendations, and Purchase Intention

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## Abstract

This thesis investigates the evolution and comparative effectiveness of product recommendation sources available to today’s consumer, focusing on the growing interplay between classical recommendations based on human interactions, and more recent ones, developed through advanced models of artificial intelligence, within the consumer decision-making process. Due to some key factors, such as rapid digitalisation, globalisation and rapid technological progress, the contemporary consumer landscape is characterised by information overload and excess of product alternatives. This situation has led individuals to increasingly rely on external sources, ranging from traditional word of mouth (WOM) to sophisticated artificial intelligence tools, to guide their purchasing choices.

To contextualize the research, a historical, sociological, and economic introduction to product recommendations is provided. More specifically, emphasis is placed on the transition from pre-digital purchasing behaviours, driven by social norms and cultural values, to today's consumer experiences, based on electronic word-of-mouth (e-WOM), influencer marketing, recommendation algorithms, and, most recently, generative artificial intelligence. This evolution is contextualized through an in-depth review of the literature and narrated through a categorization of the sources of recommendation in two primary domains: human-based (family and friends, WOM, e-WOM, social media and influencer marketing) and AI-based (recommendation algorithms, chatbots and generative AI tools like ChatGPT).

Each category is systematically examined through the lens of psychological and behavioural theories, such as trust formation, social norms, heuristics, perception of credibility and authenticity, perceived risk, supported by extensive empirical studies. The results showed that each of the sources has its own unique features and competitive advantages, which are also highly dependent on the context and type of product analysed. In general, traditional recommendations, for example from family and friends, are appreciated for their emotional closeness and perceived authenticity, which eases trust building and decreases the feeling of risk, especially in high-involvement decisions. In contrast, digital and AI-based sources offer scalability, comparability, objectivity, high availability and personalization, making them particularly useful in utilitarian or complex decision-making contexts.

The key aim of the thesis, carefully chosen based on the identification of a specific research gap, regards the direct comparison between electronic word-of-mouth (e-WOM) and ChatGPT, selected as the most effective and representative sources of their respective recommendations macro-domains. More specifically, the experimental research focuses on the electronics sector, a representative category of utilitarian goods, and aims to understand which of the two sources has the greatest ability to reduce risk perception and, consequently, to stimulate purchase intention. The results obtained show that e-WOM is more effective in decreasing the feeling of uncertainty associated with the purchase, thereby increasing the intention to buy. This most likely happens because online reviews are perceived as more authentic, reliable and emotionally

impactful due to their disinterested and genuine nature, which leads to a higher degree of psychological reassurance during the decision-making process.

On the contrary, while ChatGPT offers undoubted advantages in terms of information accessibility, speed response, analytical depth and breadth of information, its artificial nature coupled with a lower average social acceptance contributes to a higher level of risk, limiting its persuasive effectiveness in the specific context studied. These results suggest that, despite rapid advancements in the field of AI, human sources, particularly e-WOM, are even more convincing, especially in an area where the intrinsic characteristics of AI should make up a major competitive advantage.

Ultimately, the present work contributes theoretically to academic literature and enriches the theory behind managerial practice by providing a comprehensive, multidimensional understanding of how diverse types of recommendation sources influence consumer behaviour. The findings show a much more multifaceted picture than that emerged in other research concerning the effectiveness of the two sources of information analysed within this specific consumer context. Moreover, it provides useful insights for marketers seeking to optimise communication strategies and for researchers exploring the integration of emerging technologies into consumer decision-making, in a transitional era between human judgment and artificial intelligence.

# Chapter 1 – Introduction

## 1.1. A Historical, Sociological, and Economic Perspective on Product Recommendations

Before the digital revolution transformed consumer behaviour, buying decisions were much simpler and more intuitive. In a world where globalisation, e-commerce and digitalisation had not yet taken hold, consumers operated in a more limited and familiar market (Melumad et al., 2020; Aljukhadar et al., 2012; Rebitschek, 2024). The range of purchasing options was significantly more limited, considering that product accessibility was largely determined by geographical proximity and traditional distribution channels (Court et al., 2009; Mittal, 2016; Aljukhadar et al., 2012). In addition, brand loyalty was often inherited from family traditions or long-standing trust in local companies, making it unnecessary to discover alternative products. For these reasons, psychological phenomena such as choice overload were much less prevalent (Court et al., 2009; Klaus & Zaichowsky, 2021). In this context, Word-of-Mouth played a crucial role in influencing purchasing behaviour: consumers made their decisions mainly relying on opinions of friends, family and community members. Until few decades ago, personal experience stood for the primary source of product validation, especially if coming from trusted people (Brown & Reingen, 1987).

Also, traditional media used to be a highly effective marketing tool for driving consumer behaviour (Meiners et al., 2010). Brands developed credibility and established consumer trust mainly through print advertising, television commercials and in-store promotions (Pütter, 2017). These tools were particularly impactful because they stimulated consumers' brand awareness, familiarity and recall, which were one of the most important buying drivers at the time (Lemon & Verhoef, 2016; Klaus & Zaichkowsky, 2021).

Besides commercial factors, pre-digital purchasing behavior was strongly influenced by cultural and social norms within the context of the individual's background. Consumer choices were often in line with community or family standards and social influence occurred through face-to-face interaction between people close to each other, in a completely different way from today's globalized and fast-paced communication (Melnyk et al., 2021). Nowadays, all signals and stimuli coming from the surrounding environment are increasingly mixed with global trends, digital communities and online contents.

Indeed, the relative simplicity of past purchasing behaviour has been replaced by a much more complex and cognitively demanding consumer journey due to an unprecedented influx of external stimuli from a multitude of touchpoints, both online and offline (Court et al., 2009; Gupta & Mukherjee, 2024; SeoZoom, 2025; Foroughi et al., 2024). This change is generating psychological discomforts that had not previously surfaced during purchasing decisions, such as decision fatigue and the "*paradox of choice*" (Ross & Bettman, 1979; Aljukhadar et al., 2012). According to this theory, very often, the overabundance of options, instead of empowering consumers, causes anxiety and cognitive overload, delays decision-making and generates dissatisfaction and post-purchase regret (Chernev et al., 2015; Mittal, 2016; Agnihotri et al., 2024; Kim et al., 2023a; Foroughi et al., 2024). Moreover, this phenomenon can lead consumers to rely on heuristics to save mental energy (Ross & Bettman, 1979; Banker & Ketani, 2019) or even completely avoid the purchase (Mittal, 2016; Scheibehenne et al., 2010). In particular, *maximisers*, i.e. consumers who are always looking for the best choice, are the ones who suffer most from the psychological consequences of having too many product alternatives (Mittal, 2016).

It seems that the factors that most predict the occurrence of this phenomenon are the complexity of the decision-making task, a low level of knowledge of the product and an unclear structure of options (Scheibehenne et al., 2010; Chernev et al., 2015). According to some research, one of the most effective strategies for decreasing the degree of uncertainty associated with the purchasing process consists of increasing one's knowledge of the product by seeking additional information about it, both from experts and from trusted individuals (Chernev et al., 2015; Mittal, 2016).

There are countless sources of information that today's consumers can draw on to minimize the negative psychological effects of choice overload. Among the most important external stimuli useful for this purpose are opinions from peers and family members, traditional word of mouth (Hamilton et al., 2021; Reingen & Kernan, 1986), online reviews and e-WOM (Haq et al., 2024; Sulthana & Vasantha, 2019), social media and influencer marketing (Gonçalves et al., 2024; Lima et al., 2024), and recommendations generated by artificial intelligence (Kim et al., 2023a; Aljukhadar et al., 2012; Melumad et al., 2020). In the contemporary digital context, these sources represent an important decision-making support, guiding customers in navigating a market that can sometimes seem exceedingly difficult to examine independently. However, it remains in the individual's interest to understand when it is right to strategically filter information from external inputs to make more informed choices, and when it is more convenient to rely on more intuitive mechanisms, such as brand recall or heuristics. These strategies are useful for streamlining decision-making and reducing cognitive investment in particular circumstances, such as purchases characterized by *low emotional involvement* (Ross & Bettman, 1979; Sheth & Parvatlyar, 1995).

This introductory section has illustrated a historical, sociological, and economic overview of the development of product recommendations from the pre-digital era to the contemporary one. It has emphasized the progressive shift from traditional, human-driven sources to digital systems, and underlined the growing usefulness of external sources of information to cope with a more complex, broad and diverse marketplace.

#### 1.1.2. Sources of Product Recommendations

This section lists the primary sources of product recommendations accessible to modern consumers, which will be examined in more detail through the scientific literature on the subject. Furthermore, some research will be cited that attest to the usefulness of these sources in influencing consumer purchasing decisions. These are mainly surveys in which questions are asked to explore the level of consumer confidence towards various sources of information.

- Recommendations from friends, family, and traditional Word-of-Mouth

As for the first category, these are sources of paramount importance for every consumer, because they are extremely reliable due to the emotional bond and the perceived feeling of closeness with the interlocutor. They are genuine, impartial and highly personalized recommendations that can reduce the feeling of risk associated with the purchase. Word-of-Mouth, on the other hand, although it doesn't necessarily come from close sources, is the result of other consumers' experiences, and often occurs randomly and without a second purpose in everyday conversations. Due to the spontaneity with which it manifests itself and the feeling of authenticity it conveys, it has always represented a significant factor in buying decisions.

There is a vast amount of research that attests to the inestimable value of these information points in the consumer's decision-making process. According to a Nielsen report (2021), 83% of people consider recommendations from family, colleagues, and friends the highest ranked source based on trustworthiness. According to Jay Baer (2014), 92% of people trust recommendations from individuals they know directly; instead, they only trust online reviews, user-generated content, and electronic word-of-mouth (e-WOM) 70% of the time. McKinsey & Company (2010) reports that Word-of-Mouth is the primary factor behind 20% to 50% of all purchasing decisions, especially for new or expensive products. Additionally, according to a 2014 McCarthy Group survey, most Millennials (84%) prefer the above-mentioned sources of information over all types of advertising.

- Electronic Word-of-Mouth (e-WOM) (online reviews, interactions on social media, blogs and forums)

Like traditional word of mouth, it consists of genuine peer-to-peer advice based on direct personal experience with products. However, compared to the latter, it offers a much greater amount of information, available 24/7 and characterized by a higher level of customization. Thanks to its accessibility, authenticity and effectiveness, it is considered as one of the most valuable information sources of the last few decades.

According to a survey conducted by Statista in 2023, e-WOM appeared as the leading source of brand discovery in the US, compared to 32% and 21% respectively for social media and mobile app advertising. Deloitte (2014) reported that 75% of consumers said that product information found on social channels influences their shopping behaviour. Likewise, Nielsen (2025) found that 64% of Italians take online comments and reviews into account before making a purchase decision. Another study by Shopify (2024), on the other hand, shows that this percentage is as high as 90%. Furthermore, according to Spiegel (2021), compared to a product that has no reviews on the internet, a product with only 5 reviews has a 270% higher probability of being bought. Finally, according to Zhong-Gang et al. (2015), 60% of people check online reviews weekly, and 93% of them think it is a key tool for increasing the accuracy of their purchasing decisions.

- Social media marketing and influencer marketing

These are the only human sources of information analysed within this research that do not originate from other consumers, but from the companies themselves. Apart from this difference, it is necessary to examine and include them in this classification because of the immense diffusion and usefulness they have nowadays within the consumer journey. As a matter of fact, today, social media represent important points of contact with customers as they offer immediately usable and extremely useful information. They also represent a sort of cover for the company, which is why a strong and attractive presence on social networks has been essential to convey a good brand image for many years.

According to The Times (2025), 66% of consumers consider an effective social media presence to be a crucial factor in guiding their purchasing decisions. This is particularly true for platforms such as TikTok and Instagram since they have the highest engagement rates. WpBeginner (2025) shown that 43% of people turn to social network sites when they are thinking of buying a product but "do not know where to start". In an analogous way, Forbes (2023) reported that 76% of total social media users have bought something they saw on social media. Finally, according to Capgemini (2025), more than half of consumers discover new products through social media, compared to 32% in November 2022.

As for influencers, over the past 10 years they have proven to be an extremely profitable component of digital marketing, combining authenticity, emotional involvement, competence and social proof that make them amazingly effective conveyors of promotional messages for companies.

According to Statista (2023), global spending on influencer marketing reached USD 34.08 billion and it is forecasted to reach USD 39.33 billion by 2025, experiencing a 9% CAGR. According to WpBeginner (2025), 32% of Gen Z claim to have bought something they did not know existed thanks to the recommendation of an influencer. An article from Shopify (2024) states that 70% of Gen Z and Millennials usually rely on these figures to make purchasing decisions. In conclusion, according to WebFX (2025), influencer marketing can generate a ROI up to 11 times higher than traditional advertising strategies.

- Recommendation algorithms

Recommendation systems are Artificial Intelligence and Machine Learning algorithms offered by companies to help product search and improve consumer satisfaction in various contexts, including e-commerce, streaming platforms and social media. Their value derives from their ability to personalize experiences, simplify choices, increase engagement and improve decision-making. This invention has drastically changed the consumer experience, thanks to the ability of these algorithms to personalize the offer to consumers based on past preferences and behaviours.

Until 2013, 35% of purchases on Amazon and 75% of content watched on Netflix came from algorithmic suggestions (McKinsey & Company, 2013). In addition, personalised recommendations account for over 60% of listening on Spotify and generate 30% more user engagement (TechAHead, 2024). Another article by McKinsey & Company (2021) confirms the trend observed in previous years: 71% of consumers expect companies to deliver personalized interactions through algorithmic tools and "76% get frustrated when this doesn't happen". As a matter of fact, personalization in marketing can increase revenues 5 to 15% and ROI by 40% (McKinsey & Company, 2023). Finally, according to Statista (2024), 69% of companies that use AI to personalize the customer shopping experience report significant revenue growth.

- Chatbots

Chatbots are AI-powered tools available to companies to offer a range of services to consumers and improve their shopping experience. The sectors in which they are most commonly employed are e-commerce and customer service, in order to automate functions such as immediate assistance, targeted product advice, and after-sales support.

According to Zendesk (2025), chatbots can enhance operational efficiency providing 24/7 support to costumers. In fact, by relying on past preferences, they can function as personal shopping assistants, helping users to obtain personalized product recommendations, information about new products, track orders and ultimate transactions. Using these technologies, Compass, the leading real estate broker in the US, has increased its productivity, improving problems resolution rates by 9% and solving 65% of requests in a single session. In the same way, according to Tidio.com (2024), 69% of consumers are satisfied with their interactions with chatbots. Finally, according to a survey reported by Ometrics (2022), 74% of consumers prefer to interact with chatbots in the case of simple questions.

- Generative AI and ChatGPT

Recently, thanks to technological advancements, a new frontier in the field of customized recommendations has emerged: Generative AI. Despite being used for a myriad of different purposes, with the emergence of cutting-edge conversational models such as ChatGPT, since 2022, artificial intelligence has also been an effective recommendation tool in the consideration and evaluation phase of the consumer journey.

Indeed, unlike the traditional recommendation systems mentioned above, which tend to refer to historical purchasing behaviour and trends in order to make predictions, this new type of artificial intelligence acts more like a true purchasing consultant, capable of providing real-time, accurate and context-aware recommendations (Hamilton et al., 2021; Mogaji & Jain, 2024; Wong et al., 2023; Gupta & Mukherjee, 2024; Hermann & Puntoni, 2024; Kumar et al., 2025). The characteristics of this innovative technology (huge database of data, speed, accuracy, objectivity, ability to converse) make it an immensely valuable tool for consumers in their search for product information, resulting in better, faster and more personalised purchasing decisions (Hermann & Puntoni, 2024; Kumar et al., 2025; Jan et al., 2023). Although it is relatively new, research has already shown that it is setting up itself as one of the main aids for consumers when they want to find information before making a purchase.

According to Statista (2023), in 2023, over half of consumers used tools based on generative AI for product or service recommendations worldwide. Millennials were the most familiar with this type of technology, as 56% of them replaced traditional search engines with generative AI tools. According to a very remarkable report released by Capgemini in 2023, *"Why Consumers Love Generative AI"*, 68% of consumers want GenAI tools to aggregate search results from traditional search engines, social media and retailer websites to provide information on all purchase options in one place. According to Lebow (2023), "59% of US adults interested in using GenAI chatbots for shopping-related activities would use the tech for product research". Furthermore, according to a Salesforce report (2025), a 4% increase in total online sales in the United States during the 2024 Christmas season would be driven by a 42% increase in the use of artificial intelligence-powered chatbots, which would have helped consumers to purchase and return products. According to a McKinsey report (2024), 78% of companies use GenAI in at least one business function. Finally, JP Morgan (2024) found that generative AI could increase global GDP by 7-10 trillion dollars, equal to a 10% increase, becoming the protagonist and catalyst of a new wave of innovation and economic growth.

These are just some of the data that show how Generative AI is establishing itself as a powerful recommendation tool, with the potential to become a primary source of information when evaluating and considering buying choices.

In the next step, the empirical findings from the existing literature will be analysed in more detail and each of the sources of recommendations discussed will be examined individually. In particular, the sources of recommendations guided by human will be examined first, instead artificial intelligence sources will be evaluated next. Such comprehensive review of the literature will ease a better understanding of how these mechanisms operate, their respective benefits and costs as compared to each other, and how they can affect decision-making process of the consumer. This examination will conclude with the comparison of the two macro-groups to find gaps in the current literature and possible avenues for prospective research.

## 1.2. Human Sources of Product Recommendations

### 1.2.1. Social Pressure, Social Norms and Culture

It is the only "source of information" mentioned in this ranking that occurs unconsciously in the minds of consumers and does not presuppose real communication. However, it is a particularly crucial factor that has always influenced consumers' purchasing decisions. Cialdini and Trost in 1998, provided a universally accepted definition of social norms in the field of social psychology: *"rules and standards that are* *understood by the members of a group, and that guide and/or constrain social behaviour without the force of law"* (p.152).

They represent a powerful psychological mechanism through which consumers, even unconsciously, interpret information and evaluate products. When making a purchase, consumers tend to align their preferences with social expectations, the so-called *injunctive norms* (Kirmani & Ferraro, 2017), especially when this action would generate approval from their reference group (Bearden & Etzel, 1982; Bhukya & Paul, 2023; Zhou & Wong, 2008; Cascio et al., 2015; Otterbring, 2021). As a matter of fact, these unwritten rules generate implicit pressure in the consumer's mind, who will tend to follow them due to the desire for acceptance and belonging (D'Angelo et al., 2019; Escalas & Bettman, 2003; Bonfield, 1974; Bearden & Etzel, 1982; Shang et al., 2017).

In this sense, they act as cognitive shortcuts, referred to as *heuristics*, reducing the effort and time needed to decide (White & Simpson, 2012; Sheth & Parvatlyar, 1995). Notably, these factors, also known as *normative influences*, tend to exert the strongest effects on decisions that are characterized by a low emotional involvement. Indeed, in these cases consumers will rely on quicker and more superficial reasoning, trusting social proof rather than processing the available information, since these purchases are considered less important to the consumer (Fu et al., 2020). Moreover, these external influences can sometimes be so psychologically crippling that it can be complicated to make a purchase that goes against them, even when it is in line with our individual preferences (Bonfield, 1974).

However, it has been shown that vulnerability to social norms varies from person to person (Cascio et al., 2015), depending on the specific situation and the product to be purchased (Bhukya & Paul, 2023). Some consumers are more inclined to follow a consumption behaviour shared by their reference group, especially when it comes to buying publicly visible products (Bearden & Etzel, 1982; Bearden & Rose, 1990). This happens because many consumers use these products to express their social identity, which is obviously affected by external judgment (Zhou & Wong, 2008; Griskevicius & Kenrick, 2013).

Similarly, another study observed that when consumers shop in the presence of peers, they tend to choose popular brands to minimise the risk of social disapproval. The same change in consumer behaviour was not seen in the presence/absence of other people (Otterbring, 2021). In these situations, especially young people, tend to choose products that they would have ignored in the absence of the companion shopper (Lindsey-Mullikin & Munger, 2011). Regarding this topic, according to Bearden & Rose (1990), each consumer has his/her own level of *"attention to social comparison":* the higher this parameter, the more the person will tend to conform to normative expectations, especially when the purchasing behaviour is visible to others.

Like social norms, the cultural values of a community also have a considerable influence on the buying behaviour of a group of people (Bonfield, 1974; Bhukya & Paul, 2023). They stand for the set of ideals, beliefs and habits on which a community is based, and dictate what is considered desirable or necessary

(Melnyk et al., 2021; Clark & Eckhardt, 2003). For example, a study by Jakubanecs et al., (2022), showed that brand competence has a greater influence on purchase intentions in individualistic cultures than in collectivist cultures. In the latter, it was more effective to emphasize the brand's warmth and social connection.

### 1.2.2. Opinions from Friends, Family and Traditional Word-of-Mouth

Social norms manifest themselves through the need to conform to social and cultural expectations and to the pressure of a group (Bonfield, 1974). This phenomenon happens on an unconscious level and does not require direct interaction. This second paragraph will examine the opinions and recommendations coming from family and peers, and more generally the traditional Word-of-Mouth (WOM). In this case, a voluntary and direct conversation takes place aimed at finding information and input for the purchase decision (Singh & Nayak, 2014).

First, it must be said that there are major differences between advice from friends and family and conventional Word-of-Mouth. In the former case, the advice is generally considered impartial and reliable due to shared interests, a strong personal bond and mutual trust (Reingen & Kernan, 1986). Suggestions coming from these sources are extremely effective because of the low social distance perceived with the interlocutor (Hamilton et al.,2021). Moreover, the feeling of closeness experienced from conversing with a trusted person increases the consumer’s confidence, making the advice more captivating (Faraji-Rad et al., 2015). Also, the absence of persuasiveness and ulterior motives from these sources makes them highly trustworthy (Gupta & Chundawat, 2002; Millard & Thomas, 1984; Fitzsimons & Lehmann, 2004). Many studies have also shown that advice from friends and family plays a decisive role in stimulating purchasing behaviour by significantly reducing the risk perceived by consumers (Zirena-Bejarano & Zirena, 2024; Kirmani & Ferraro, 2017; Bearden & Etzel, 1982). These tips can also amplify the positive effect of e-WOM on purchase intentions (Kour et al., 2024; Haq et al., 2024; Fitzsimons & Lehmann, 2004). In addition, when a negative review comes from these close sources, it seems difficult to counteract its effect even in the presence of a broad positive consensus in online discussions (RV & Varshney, 2022).

For the reasons mentioned above, friends and family are highly valued sources of information (Hamilton et al., 2021). More in particular, advice from these people, called *strong ties*, are preferred when the decision-making task is characterized by a high perceived risk and when there is no in-depth knowledge of the product (Duhan et al., 1997). Communication between peers through social media, especially when there is a strong bond, creates greater consumer involvement with the product, which in turn increases the intention to buy (Wang et al., 2012). In the same way, according to a study by Argo & Dahl (2000), interactions with close ties often generate higher spending and are associated with increased positive retailer evaluations. Furthermore, these recommendation sources are also preferred for short-term purchasing decisions, as they are perceived as more practical and specific (Zhao & Xie, 2011). Interactions between peers, especially among teenagers, play a significant role in increasing the intention to purchase products for the family too (Jin & Wang, 2017). More in detail, this factor seems to have a greater influence in the first stages of the purchasing process, such as the search for information (Singh & Nayak, 2014).

The level of importance attributed to the opinions of the external reference group also varies according to culture: it has been demonstrated that the influence of peers is stronger in industrialised countries with an individualistic culture (for example the United States), while the family seems to be the primary source of information in countries characterized by a collectivist culture, such as Thailand (Childers & Rao, 1992). However, decisions regarding publicly visible products are strongly affected by the consumption behaviour of the reference group, regardless of country. This phenomenon is particularly noticeable in more affluent contexts with greater cultural exposure, which show a higher level of conformity to the opinions of peers (Khan et al., 2016). As previously mentioned, in addition to being a reliable source of direct recommendations, peers also act as a behavioural model, as young people often imitate the habits and purchasing choices observed within their social circles (Harwanto et al., 2020).

On the contrary, Word-of-Mouth distinguishes itself from the afore-mentioned sources in several key respects. As a matter of fact, it can take place in any social context, it can be represented by the opinion of complete strangers, and can also occur casually, not always having the specific purpose of helping someone make a purchase. For these reasons, information coming from this channel is generally characterised by a lower degree of personalisation than the previous one (Cruz et al., 2017).

A universally accepted conceptualization in literature defines Word-of-Mouth (WOM) as *"informal communications directed at other consumers about the ownership, usage, or characteristics of particular goods and services and/or their sellers"* (Westbrook, 1987, p. 261; De Matos & Rossi, 2008).

Traditional word-of-mouth is widely recognised as one of the most useful and reliable sources of information for consumers (Brown & Reingen, 1987; Richins & Root, 1988). Compared to advertising, social media marketing and influencer marketing, it originates from real consumer experiences and has no commercial purposes. For these reasons, it is generally perceived as a unbiased opinion aimed at sharing information and raising knowledge about a product/service which has been appreciated (Walsh & Mitchell, 2010; Huete-Alcocer, 2017; Court et al., 2009; Cheong & Morrison, 2008; Chang & Chin, 2010). Furthermore, it stems from social ties, both strong and weak, and from face-to-face communication, which contribute to its trustworthiness (Hogan et al., 2004).

It is seen as a highly genuine and useful source for obtaining information because it naturally takes place in everyday conversations. In addition, it seems to be a very effective tool during the evaluation and consideration phases of the consumer journey in reducing the level of uncertainty and the perceived risk associated with the purchase of a product (Lemon et al., 2016; Duhan et al., 1997). One study has shown that in emerging markets offline sources of product recommendation (both strong and weak ties) are still crucial, while in developed economies there is a tendency to rely more on information found on the internet during the purchasing process (Goodrich & De Mooij, 2013).

Moreover, there is existing research that testify to the effectiveness of WOM when used by businesses as a marketing tool. It has been shown that in every network of people there is one or more opinion leaders, whom companies should invest in, as they can act as potential referral multipliers (Reingen & Kernan, 1986; Meiners et al., 2010; Rosen, 2001). In fact, in certain cases they can become more effective than the more well-known influencers, because of the lower social distance perceived by consumers (Haenlein & Libai, 2017). Finally, several studies show that WOM is more effective than traditional advertising tools, having a greater and longer-lasting impact on a company's acquisition of new customers (Trusov et al., 2009; Hogan et al., 2004; Villanueva & Hanssens, 2008).

### 1.2.3. Electronic Word of Mouth (e-WOM)

The phenomenon of Electronic Word-of-Mouth (e-WOM) emerged in the early 2000s with the spread of the Internet and digital platforms. It immediately became a powerful communication tool between consumers and producers (Sharma et al., 2011; Gonçalves et al., 2024; Dwivedi et al., 2020) and a vehicle for facilitating the exchange of opinions among consumers (Gunawan & Huarng, 2015; Gonçalves et al., 2024; Klaus & Zaichkowsky, 2021; Deloitte, 2015). Among the key features that differentiate it from the above sources of information are the 24/7 accessibility and the considerably greater amount of information that can be found within (Melumad et al., 2020). Compared with the traditional WOM, which is restricted to well-defined geographic boundaries, e-WOM manifests itself with a considerably larger number of participants, active and passive, and a significantly greater quantity and quality of information cues (text, pictures and videos) (Zhao et al., 2017). These peculiarities make it an extremely exhaustive and immediate tool to use. It can manifest itself in various forms, including online reviews, comments posted on social media, and content found on blogs and forums (Hennig-Thurau et al., 2004).

Online reviews are positively correlated with an increase in purchase intention among consumers who use them (Haq et al., 2024; Sulthana & Vasantha, 2019). This process can occur both directly and indirectly through brand awareness (allowing the brand to reach more people) and trust (as mentioned, consumer-to-consumer recommendations are generally perceived as more reliable than advertising) (Haq et al., 2024). E-WOM can also increase sales of a product (Roy et al., 2017; Buttle, 1998), especially in the short term (Moe & Trusov, 2011). For example, in the movie industry, the amount of e-WOM about a movie seems to increase sales more than the objective value of the movie and traditional advertising expenses (Kim et al., 2022). However, negative reviews are perceived as more credible (Chatterjee, 2001) and have a proportionally greater effect on sales than positive ones (Chevalier & Mayzlin, 2006).

Also, the use of online content and advice decreases the perceived risk experienced during the buying process (Chen et al., 2015; Kour et al., 2024; Kirmani & Ferraro, 2017; Sharma et al., 2011) or even encourage riskier purchasing behaviour, increasing the feeling of support and protection. This is especially true when there is a strong connection with the author of the review (Yang, 2022), as can happen in online forums (Zhu et al., 2012; Fu et al., 2020). Even, earlier reviews by other consumers can also mentally influence the effect of positive and negative experiences with the product (Sridhar & Srinivasan, 2012).

Specific product and consumer characteristics shape the perceived level of usefulness of this informational source (Cascio et al., 2015). For example, when choosing the source of information on a particular product, consumers seem to prefer online reviews, as they are more structured and detailed, compared to information on social media. Conversely, the willingness to use the latter increases when there is uncertainty about the product one is interested in or when there is a difficulty in evaluating the product itself (Bartschat et al., 2021). It has been demonstrated that the quality and quantity of positive interactions on social media regarding a product increase the intention to make an impulse purchase due to a perceived popularity of the product, especially for products with low emotional involvement (Huang et al., 2025). In the video game sector, however, it seems that online reviews related to less popular products increase sales more than those of more popular video games (Zhu & Zhang, 2010).

Some specific characteristics of online reviews are more likely to generate high purchase intent. The quality of the information provided, and the perception of credibility are highly effective factors in increasing purchase intention (Erkan & Evans, 2016; Ismagilova et al., 2019). The factors that most predict the use of online reviews seem to be the positive valence of the message (De Bruyn & Lilien, 2008; Zangeneh et al., 2014; Kour et al., 2024; Haq et al., 2024), costumer product ratings (De Langhe et al., 2015), information accuracy (Roy et al., 2018; Filieri & McLeay, 2014; Lee & Shin, 2014; Cao et al., 2010; Chatterjee, 2001; Leong et al., 2021) and perceived credibility of the source (Zhang et al., 2014; Chen et al., 2015; Gunawan & Huarng, 2015; Kour et al., 2024; Leong et al., 2021).

On websites that allow to establish the perceived competence of the reviewer (which act on the so-called *peripheral route*), for example through a rating or number of followers, these metrics also significantly increase the usefulness of the review (Majumder et al., 2022; Cheng & Ho, 2015). The amount of information contained in the review is considered less important by the average consumer (Filieri, 2014). Instead, the significance of the quantity of reviews as a predictive factor of purchase intention has been proven (Ali & Cai, 2018; Rosario et al., 2016), but not in all the studies analysed. As regards the differences between the genders, women generally show a higher level of trust in online recommendations. However, both of them seem to trust reviews with mixed valence (neither positive nor negative) more than completely positive or negative ones (Prendergast et al., 2016; Doh & Hwang, 2008).

As mentioned previously for traditional WOM, this tool is also generally preferred to traditional advertising as it is perceived as more authentic and genuine (Bickart & Schindler, 2001; Sulthana & Vasantha, 2019; Smith et al., 2005; Meiners et al., 2010; Rosen, 2001; Helm, 2000; Court et al., 2009; Cheong & Morrison, 2008; Bahtar & Muda, 2016; Godes & Mayzlin, 2004). However, Chen et al., (2015), found that consumers who are less susceptible to *informational influence* tend to weigh the information gained from user-generated content with other forms of data, including company's own information.

### 1.2.4. Social Media Marketing and Influencer Marketing

Nowadays, with the spread of social networks, social media marketing and influencer endorsements are one of the most important means for companies to reach consumers, especially the younger ones (Gen Z and Millennials) (Lima et al., 2024; Vrontis et al., 2021; Samsudeen & Kaldeen, 2020; Dwivedi et al., 2015; Ansari et al., 2019). Digitalization has transformed marketing, with platforms such as Facebook, Instagram, Twitter, YouTube and LinkedIn offering unprecedented opportunities to catch consumers (Pütter, 2017). Through these applications, marketers can easily access the daily lives of consumers, offering micro-experiences that increase engagement and brand loyalty (Güngör et al., 2024). Moreover, social media marketing is cheaper than traditional marketing, offers superior targeting capabilities and allows direct, real-time interaction with customers (Khanom, 2023; Kaplan & Haenlein, 2010).

According to Weinberg (2009) definition, social media marketing is *"an integrative process aimed at promoting goods and services over platforms of social media, which has the potential to target a far wider consumer base in comparison to the traditional forms of marketing".*

Based on a thorough review of the literature, it appears that the most effective strategies for stimulating purchases through this recent marketing tool are: interactive, captivating and preferably short content to involve the public such as contests, surveys and quizzes (Sokolova & Kefi, 2019; Meliawati et al., 2023; Pütter, 2017), promotions and direct interactions with the brand (Lima et al., 2024; Gonçalves et al., 2024; Kim & Ko, 2010; Ye et al., 2021; Chetioui et al., 2020; Laksamana, 2018; Husnain & Toor, 2017; Moslehpour et al., 2021). Among other factors, the relevance of the information provided, and the credibility of the advertisement are also important (Alalwan, 2018; Hanaysha, 2022; Ceyhan, 2019; Samsudeen & Kaldeen, 2020), in an analogous manner as seen for e-WOM.

Marketing strategies conducted through these platforms are significantly correlated with an increase in brand loyalty (Ceyhan, 2019), which in turn makes consumers more likely to buy the brand (Balakrishnan et al., 2014; Almohaimmeed, 2019; Hanaysha, 2022; Sanny et al., 2020). Some studies have shown that social media marketing activities increase purchase intention through the mediated effect of three components: brand trust (Kim & Ko, 2010), brand experience and finally brand love (Koay et al., 2023).

As regards to influencers, thanks to their ability to create authentic and engaging content, they usually generate greater trust, credibility (Sokolova & Kefi, 2019), brand awareness and engagement than traditional advertising (Leung et al., 2022; Li & Peng, 2021), increasing consumers' intention to purchase (Vrontis et al., 2021; Ye et al., 2021). Purchase intention is also significantly enhanced in an indirect way through certain mediators such as quality information, trust toward influencers, perceived credibility (Müller et al., 2018; Chetioui et al., 2020; Babu et al., 2024; Li & Peng, 2021; Koay et al., 2021; Lim et al., 2017), perceived authenticity (Hermanda et al., 2019) and attitude toward sponsored contents (Tiwari et al., 2024; Harison & Lahav 2024; Gomes et al., 2022; Saima & Khan, 2020; Bhagat et al., 2024). The number of followers and the influencer's popularity also seem to have the same effect (Weismueller et al., 2020). Influencers also have the power to amplify e-WOM about a specific company, reaching new audiences through content sharing (Ye et al., 2021).

The alignment between the influencer's image and the consumer's self-concept also appears to have a significant impact on the consumer's purchase intention. According to diverse research, the feeling of similarity with these figures amplifies the persuasiveness of their advice (Hermanda et al., 2019; Li & Peng, 2021; Lim et al., 2017). In addition, creating a *parasocial interaction* with these people, i.e. a unilateral bond similar to friendship, also raises the consumers' inclination to follow their purchasing recommendations, through the greater perceived emotional connection (Sokolova & Kefi, 2019; Harison & Lahav 2024; Gomes et al., 2022; Yuan & Lou, 2020). In this context, it has been observed that the credibility, transparency and social attractiveness (Jansom & Pongsakornrungsilp, 2021; Babu et al., 2024) of the influencer seem to be the most predictive factors in the establishment of this relationship (Yuan & Lou, 2020).

Furthermore, it seems that *advertising disclosure*, or the declaration of sponsorship, also enhances the intention to purchase, enhancing the influencer's attractiveness (Weismueller et al., 2020; Gonçalves et al., 2024; Duffek et al., 2025; Kay et al., 2020). This is probably because in this way they are perceived as more authentic. In particular, it has been shown that even a micro-influencer who discloses sponsorships generates higher purchase intentions than a macro-influencer who has not disclosed (Kay et al., 2020).

Finally, some research emphasizes that, as with other sources of recommendation mentioned above, an information overload from social media influencers' contents can cause confusion, stress and even avoidance of the purchase (Agnihotri et al., 2024). However, as the vastness of information is an intrinsic characteristic of the contemporary digital world, other sources of information can also cause the same discomfort. It is therefore not to be considered as a weakness belonging only to this category of product recommendations.

### 1.3. AI Sources of Product Recommendations

#### 1.3.1. Brief History and Introduction of Artificial Intelligence

With the introduction of Asimov's *Three Laws of Robotics* and the publication of *Computer Machinery and Intelligence*, the idea of developing autonomous and intelligent machines began to gain ground (Haenlein & Kaplan, 2019). However, the term Artificial Intelligence (AI) dates back only to 1956, when John McCarthy and his colleagues defined it as *"the science and engineering of making intelligent machines, especially* *intelligent computer programs"* (McCarthy, 2004, p.2). This event marks the beginning of scientific research on AI. This technology is also defined also as *"a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation"* (Haenlein & Kaplan, 2019) (p.6).

Artificial intelligence went through distinct stages of development, each characterized by significant innovations and practical applications. However, also due to reduced funding, technological discoveries in this new branch of science were slow to come (Haenlein & Kaplan, 2019). In the 1990s, the invention of *Machine Learning* gave rise to algorithms capable of learning from data, leading to advances in predictive analysis and personalization, such as the recommendation engines used by Netflix and Amazon. This technological advancement represented one of the first important uses of AI in the field of marketing. However, the true rebirth of AI occurred in 1997, when IBM's *Deep Blue* robot defeated world chess champion Garry Kasparov, proving the potential of *Expert Systems,* and above all in 2006, when systems based on *Deep Learning* were developed for the first time. This recent technology revolutionized image recognition, natural language understanding and advanced automation thanks to deep neural networks, favouring innovative applications such as self-driving cars and intelligent virtual assistants (Haenlein & Kaplan, 2019). Finally, the advent of generative AI has added a creative dimension to AI, enabling automatic content generation and new ways of interacting with consumers. For companies, these technologies have opened up new opportunities in marketing, product development and advanced data analysis (De Bruyn et al., 2020; Sinha et al., 2023).

Today, AI is a key strategic resource for improving the operational efficiency of companies, offering personalized experiences to consumers and driving innovation in numerous sectors (Chintalapati & Pandey, 2021). This extremely powerful tool is transforming marketing, allowing firms to analyse huge amounts of customer data, offer tailored contents and products based on past preferences and behaviour, and automate decisions and processes to improve the effectiveness of campaigns (Kumar et al., 2019; Haenlein & Kaplan, 2019; Harkness et al., 2023).

The main danger is that managers overestimate the capabilities of AI or underestimate its risks (De Bruyn et al., 2020). One of the main problems related to AI for marketers and consumers is the *"incomprehensibility"* of this technology: it is based on *formal rationality* (data and statistics) rather than on *substantial rationality* (deep understanding of customers and their motivations). In other words, this tool is extremely precise in identifying complex patterns among gigantic amounts of data, but it is not capable of explaining them (Haenlein & Kaplan, 2019). For this reason, it is necessary to avoid total dependence on this technology (Alexander et al., 2018) and try to humanize its output as much as possible (Kozinets & Gretzel, 2020; De Bruyn et al., 2020). Many studies show that human skills and artificial intelligence should work together rather than replacing each other to maximize the effectiveness of business operations and marketing campaigns (Davenport et al., 2019; Haenlein & Kaplan, 2019). Finaly, another fundamental problem linked to this technology is represented by data security and privacy, as these technologies collect and use personal data without consent (Labrecque et al., 2024; Abou-Shouk et al., 2024; Brill et al., 2019).

In this section the most important applications of Artificial Intelligence in the field of marketing will be discussed, starting with recommendation algorithms, through conversational chatbots, and ending with Generative AI. In particular, as done for human sources of information, the main papers on each of these AI tools will be analysed, trying to extrapolate their advantages and shortcomings in the context of product recommendations.

### 1.3.2. Recommendation Algorithms

Recommendation systems, also called *Recommendation Agents (RAs),* are predictive artificial intelligence algorithms that analyse user data (such as preferences, past behaviours and demographic characteristics) to suggest personalized products, services or experiences. They began to proliferate at the late 90s, particularly when Amazon introduced its innovative collaborative filtering system in 1998, which immediately became its trademark. They are now widely used in e-commerce websites (es. Amazon, eBay, Zalando), streaming platforms (es. Spotify, Netflix) and social media (TikTok, Instagram).

Traditionally, these algorithms use three main approaches to personalise users' experiences: *collaborative filtering* (suggest items based on the preferences of similar users), *content-based filtering* (recommend products based on past preferences and user's characteristics), or a *hybrid approach* (combine both to optimize the effectiveness of the recommendations) (Al-Hasan et al., 2024).

In the context of e-commerce, recommendation algorithms have been proven to offer substantial benefits to businesses. By expanding the consumer's *consideration set* (Li et al., 2021), these technologies have the ability to increase purchase intent and average cart value. Among the advantages offered to consumers through the use of these tools are a substantial reduction in information overload, which occurs through a significant decrease in the time spent searching for products and a smoother purchasing process (Aksoy et al., 2011; Aljukhadar et al., 2012; Xiao & Benbasat, 2007; Hermann & Puntoni, 2024). They represent a remarkably effective tool due to the excess of information present in digital marketplaces, which often leads to the need to use cognitive shortcuts to reduce the level of difficulty of the choices (Banker & Khetani, 2019).

However, trust in these algorithms is crucial to ensure their use and acceptance by consumers. This factor strongly depends on the quality of the advice (composed of several elements, including accuracy, novelty and diversity), transparency of the suggestions (making users understand why a particular product is recommended) and the quality and usability of the website interface (Aksoy et al., 2011; Xiao & Benbasat, 2007). In turn, a satisfactory level of trust increases the purchase intention (Nilashi et al., 2016). The perceived usefulness, information richness, and degree of personalization offered by recommendations also seem to play a key role in the acceptance of such systems (Jan et al., 2023; Komiak & Benbasat, 2006). Furthermore, familiarity with these algorithms is also essential in building consumer trust, both emotional and cognitive (Komiak & Benbasat, 2006).

As previously mentioned, AI is often perceived as a *“black box”*, as it is not always possible to understand how it makes decisions and reaches certain conclusions. In this regard, an interesting study analyses the effectiveness of *post-hoc explanations* offered by artificial intelligence, i.e. clarifications or justifications concerning the reason behind a recommendation. It has been proven that this kind of explanations increase the perception of interpretability of algorithm advice (giving the illusion of *“opening”* that black- box), strengthening trust, and purchase intention (Chen et al., 2024). This positive effect seems to be more pronounced in utilitarian decision-making contexts than in hedonistic ones. Also, *attribute-based explanations,* which are based upon the *“content-based filtering”,* are more effective in utilitarian domains, while user-based explanations, based upon *“collaborative filtering”,* work better in hedonic contexts (Chen et al., 2024). In addition, user-based collaborative filtering seems to be more appreciated by people who are experts on a specific product, as they can evaluate the accuracy of the recommendations (Chinchanachokchai et al., 2021).

From another noteworthy research regarding this subject, it also seems that Recommendation Agents improve customer satisfaction and purchase intention when they think in a similar way to the customer: in particular, this happens when there is resemblance in the way the attributes of the products are weighted (price, quality, etc.) and in the decision-making strategies (e.g. compensatory rules vs. heuristics) (Aksoy et al., 2006). This discovery proves that knowing the cognitive processes behind consumers' buying behaviour can be a significant competitive advantage in personalizing buying experiences.

However, recommendation algorithms have not been free from criticism over time, especially since more efficient personalization systems have been developed due to technological progress. According to the *“information cocoon”* theory, these algorithms would lead to less optimal purchasing choices in the long term. Since AI tends to suggest products that are similar to each person's tastes, the algorithm would prevent the exposure to different products, thus hindering the comparison and discovery of better alternatives over time (Chen et al., 2021; Melumad et al., 2020). Furthermore, it is not uncommon for AI to misinterpret data, providing incorrect suggestions, or to excessively influence search criteria, limiting the user's freedom of choice (Gao & Liu, 2022). Among the problems intrinsically linked to the functioning of this specific category of AI tools are *cold start* (difficulty in suggesting products to new users or new products to existing users), *scalability* (inability to maintain good performance as the database grows), and limited personalization of the consumer experience compared to more recent AI systems (Al-Hasan et al., 2024; Ji et al., 2024; Luo et al., 2024).

### 1.3.3. Chatbots

Chatbots are defined as *"software programs that interact with users using natural languages, simulating a human conversation"* (Shawar & Atwell, 2007, p. 29). The first ones to become widespread employed a *Rule-based technology*, elementary models which gave programmed answers to specific questions. The most successful ones were developed in the early 2000s and were based on a Machine Learning technique called *Natural Language Processing (NLP)*. They understand natural language, adapt themselves to the context and improve over time, offering more fluid, flexible and intelligent conversations. This technology is used to provide assistance and perform automated operations in sectors such as e-commerce, customer service, healthcare and banking.

In the context of customer service, chatbots have the advantage of giving immediate assistance at any time of the day reducing business costs and personalizing responses based on past interactions (Misischia et al., 2022; Fleischner & Grad, 2019; Chong et al., 2021; Inavolu, 2024). They are often used by firms as the first point of contact to try to automate the simplest requests (Nordheim et al., 2019). As a matter of fact, they are particularly effective in carrying out easy activities such as receiving reservations and feedback (Leung & Chan, 2020). In this field, user satisfaction is extremely dependent on the use of clear and concrete language, perceived usefulness of the information (Jimenez-Barreto et al., 2023), ease of use, responsiveness (Chen et al., 2021) and problem-solving capacity of these tools (Hsu & Lin, 2022; Nordheim et al., 2019; Rapp et al., 2021).

Within the context of online shopping, they appear to be beneficial in helping consumers to analyse and compare products to make more informed decisions (Silva et al., 2023). The development of *conversational commerce*, namely the process of buying products through voice or text interactions with artificial intelligence (AI), is revolutionizing the online shopping experience, enhancing decision speed and making it more efficient (Balakrishnan & Dwivedi, 2021; Silva et al., 2023). According to a study on Emma, the chatbot of Zalando, the most principal factors that predict the usage of this chatbot are the conversational naturalness and the perceived usefulness when searching for product-related information. Nevertheless, many respondents perceived the chatbot to be cold, unable to effectively recognize consumer requests, and less useful as a service agent than a human employee (Rese et al., 2020). Even when shopping, these tools are preferred to receive advice on simple, low-involvement tasks (Hsu et al., 2023).

A much-debated topic in the literature concerns the level of anthropomorphising of chatbots. Several studies have shown that the more an algorithm seems similar to humans, the more it generates trust and purchase intent (Blut et al., 2021; Schanke et al., 2021; Pelau et al., 2021; Wei et al., 2024; Adam et al., 2020; Chong et al., 2021; Nordheim et al., 2019; Rapp et al., 2021). This effectiveness does not appear to vary between utilitarian and hedonic contexts (Konya-Baumbach et al., 2022). The chatbot is considered anthropomorphic when uses emotional expressions and imitates human empathy (Pelau et al., 2021; Rapp et al., 2021), has a human voice (in the case of AI voice assistants) and personalizes responses by remembering past preferences. However, even an anthropomorphic chatbot with poor conversational skills can generate disappointment (Go & Sundar, 2019). Instead, on average, non-anthropomorphic chatbots increase the *psychological reactance* to advice, especially if they are activated automatically, leading consumers to ignore them. This makes choice more difficult and less immediate, but can also lead to greater satisfaction, as the consumer feels they have thought more independently about their choice (Pizzi et al., 2020).

At the same time, too much human-like behaviour leads to a decreasing of user confidence and acceptance of such tools, due to the feeling of uneasiness generated, called the *"uncanny valley"* effect (Blut et al., 2021; Wei et al., 2024; Chakraborty et al., 2024; Chong et al., 2021; Fernandes & Oliveira, 2020; Kim et al., 2019; Przegalinska et al.. 2019; Castelo et al., 2019). However, the higher a user's level of expertise, the less the level of humanization of the chatbot appears to influence the generation of trust (Greiner & Lemoine, 2025).

In addition to textual chatbots, consumers are increasingly delegating their purchasing decisions to AI voice assistants (e.g. Amazon Alexa, Google Assistant and Apple Siri). The factors that most predicts the use of such instruments are the elimination of information overload, reduction of research time, personalization of responses (Rhee & Choi, 2020) and the feeling of a human conversation (Klaus & Zaichkowsky, 2021). Also in this case, the perceived usefulness, quality of information (Silva et al., 2023; Fernandes & Oliveira, 2020), enjoyment and ease of use are decisive in increasing the intention to use these technologies (Kasilingam, 2020; Romero-Charneco et al., 2024). As with textual chatbots, anthropomorphism and perceived intelligence are also crucial for increasing the propensity to follow advice (Balakrishnan & Dwivedi, 2021). From a study by Yang et al., (2024), the fluency of human-AI voice interaction (e.g., with Alexa) increases online purchase intention through the mediated effect of perceived warmth and competence. Specifically, in scenarios with low certainty or product involvement, warmth is more influential in driving purchase decisions, and vice versa. In the context of *conversational commerce*, chatbots with anthropomorphic traits increase the perception of personalization and willingness to pay a higher price, and situational solitude when interacting with these tools can amplify this effect even more (Sidlauskiene et al., 2023).

Since the voice is a distinctive element of this category of chatbots, the characteristics of the latter also have important effects on the user's confidence. Firstly, a friendly rather than formal tone is generally preferred (Rhee & Choi, 2020; Rese et al., 2020). In particular, a warm tone seems to be more effective for experiential products (e.g. hotels and travels) and for present-oriented consumers. Instead, chatbots that show a competent tone seem to be preferred for technological products and by future-oriented consumers (Roy & Naidoo, 2020). Moreover, recommendations of chatbots with a male voice are more convincing when the product is utilitarian in nature, and those with a female voice are more persuasive for hedonistic products (Ahn et al., 2021). Another study shows that chatbots with female characteristics are considered more human and therefore more accepted (Borau et al., 2021).

In the luxury sector, the customer experience and satisfaction improve when interactive chatbots provide advice characterized by personalization, accuracy of information and quality of communication (Shahzad et al., 2024). However, in this field too, these tools seem to work better for providing basic assistance, rather than completely replacing human advice (Chung et al., 2018; Leung & Chan, 2020).

An important meta-analysis on the subject showed that, regardless of the purpose, the most decisive factors for the adoption of chatbots are perceived usefulness, attitude towards this technology and level of trust (Li et al., 2023). As with other AI technologies, transparency is crucial for these systems too (Przegalinska et al., 2019). Also, it seems that the degree of acceptance and satisfaction deriving from chatbot advice increases when the consumer already has a clear idea of what they want, especially for utilitarian products (e.g. electronics, household appliances) (Zhu et al., 2022).

Companies have invested heavily in conversational AI, but many implementations have not been really appreciated by users worldwide (Greiner & Lemoine, 2025). As a matter of fact, there is still a lot of resistance from consumers regarding usefulness of chatbots due to a quality and personalization of the service that often does not meet expectations (Chong et al., 2021; Jimenez-Barreto et al., 2023).

Like said before, they still have limited ability to understand and interpret human language, making them less useful for complex decisions (Leung & Chan, 2020). They often display errors of interpretation, lack of consistency in their answers and an inability to manage long conversations (Rapp et al., 2021). Many consumers expect better performance than they receive from the main AI voice assistants on the market (Siri, Alexa & Google Assistant) (Brill et al., 2019). In general, they are often perceived as *too artificial* and incapable of understanding the meaning of words in depth (Go & Sundar, 2019). In addition, the feeling of risk to the security of personal data arising from the use of chatbots is quite common among users (Silva et al., 2023). Finally, as with other types of AI algorithms, there is also a demand for greater transparency in the responses, as it represents a predictive factor of the use of these technologies (Przegalinska et al., 2019).

Considering the scientific results obtained, it can be stated that chatbots have improved user experience by automating and optimizing various business activities, including technical and after-sales support. However, these tools are still limited to basic functions, presenting problems in text comprehension, adaptability, and complex problem solving, often making interactions with consumers unsatisfactory and cumbersome.

#### 1.3.4. Generative Artificial Intelligence

Generative AI is a type of Artificial Intelligence that creates content (e.g. text, images, music, videos) starting from a first input. It is designed to generate responses, design outputs or invent ideas, based on Machine Learning models that have assimilated enormous amounts of pre-existing data. Compared to classic predictive AI, which analyses structured data to make predictions, this innovative technology can create contents from such data (Grewal et al., 2024). It has practically infinite applications including marketing, service operations, banking, hospitality, healthcare, education, manufacture and software engineering (Dwivedi et al., 2023; McKinsey, 2024; Ooi et al., 2023). In the field of business, companies are adopting GenAI to generate advertising copy, personalize offers and automate customer service (Brand et al., 2023; Sinha et al., 2023).

More in detail, ChatGPT has revolutionized the way people interact with technology, becoming one of the most popular GenAI tools (Ooi et al., 2023). It falls within the *Large Language Models* (LLMs), a sub-category of GenAI algorithms, which are trained on huge databases of textual data. The most appreciated characteristics in its answers are accuracy, relevance, perceived usefulness and speed (Niu & Mvondo, 2023; Ma & Huo, 2023).

Recommendation systems have evolved significantly in recent decades, moving from methods based on collaborative filtering and content-based filtering to more advanced Deep Learning models. Today, generative artificial intelligence offers new opportunities to improve personalization marketing, possessing far greater computing capabilities than previous technologies. This tool is capable of much more intelligent interactions with users, improvements in data representation, ranking and evaluation of recommendations (Wang et al., 2024; Al-Hasan et al., 2024; Ji et al., 2024; Kumar et al., 2025; Hermann & Puntoni, 2024).

For these reasons, generative AI is transforming crucially the decision-making process of buyers, allowing quick access to detailed product information (Iranmanesh et al., 2024). Being a conversational AI, users can express their needs in natural language and the system can provide detailed explanations of the advice given and change the recommendations ongoing (Al-Hasan et al., 2024; Gupta & Mukherjee). In addition, the risk of the *"filter bubble"* that occurred with traditional recommendation system models is eliminated, favouring the discovery of new product alternatives (Wang et al., 2024).

The factors that most predict the adoption of generative AI and ChatGPT to obtain information about purchases, compared to other available options, are the perceived competence, accuracy and personalization of the responses, ease of use, perceived fun, and transparency of information (Iranmanesh et al., 2024; Pathak et al., 2024). In the online grocery shopping sector, the quality of interaction, the perceived reliability of information, and a moderate degree of anthropomorphising significantly increase trust in GenAI algorithms (Chakraborty et al., 2024). A study on the impact of GenAI on the adoption of e-commerce chatbots has shown that this new technology, compared to predictive AI, makes these tools much more effective and anthropomorphized, which increases user satisfaction (Arce-Urriza et al., 2025; Kumar et al., 2025).

ChatGPT turned out to be more effective than Amazon's recommendation system in building trust and guiding consumers towards purchase: products recommended by this technology were more likely to end up on the list of products considered by consumers than those suggested by *Amazon Personalize*. That's because GenAI was seen as more accurate, transparent and neutral in its recommendations (Chang & Park, 2024). Another experiment showed that ChatGPT is much more useful than traditional e-commerce recommendation models in advising products to consumers. In particular, the CTR, conversion rate and average user satisfaction have increased significantly (Malikireddy, 2024).

Also, when ChatGPT provides product-related recommendations, contrary to the theory of choice overload, customer satisfaction and purchase intention are even directly proportional to the number of options proposed by the AI. Since this tool is perceived as highly accurate and personalized, the number of recommended alternatives, although excessive, is well accepted and the usual negative effects deriving from having too many choices are significantly mitigated (Kim et al., 2023a). The given output is not interpreted as a sign of confusion, but of greater depth and knowledge of the AI.

Generative AI is also revolutionizing the hospitality and tourism sector. More and more people are relying on GenAI advice to get more detailed and personalized information for their travel plans. Here too, the relevance, credibility and usefulness of the information, and the perceived intelligence of the AI assistant (how much it seems to understand the user's questions and travel preferences) are the factors that most predict the use of this new technology (Wong et al., 2023; Ali et al., 2023). Trust then increases the intention to put the advice given by ChatGPT into practice (Ali et al., 2023; Abou-Shouk et al., 2024). Also, the employment of figurative language, which leads to greater vividness of mental images, and the perception of AI as similar to a human being are significantly correlated with an increased intention to visit the recommended destinations (Baek et al., 2025). However, it is not uncommon for ChatGPT to make mistakes and give erroneous information about travel information, which obviously significantly decreases the intention to follow the advice (Kim et al., 2023c).

Although it is undeniable that enormous steps forward have been made compared to previous AI models in terms of perceived usefulness and accuracy of the information provided, in light of current research results, it seems clear that even an advanced technology like GenAI is not infallible. In fact, it often gives the *“illusion of intelligence”,* producing coherent and plausible texts, but without utterly understanding the underlying content. It is also prone to *hallucinations,* often giving nonsensical output, with factual errors and invented citations (Monteith et al., 2024; Paul et al., 2023; Dwivedi et al., 2032; Wen & Laporte, 2025). In this sense, it can also be a dangerous means of misinformation, accessible to anyone (Balta et al., 2025).

Furthermore, as a recommender system, ChatGPT displays some important limitations: it does not always correct mistakes or ask for clarification, sometimes struggles to connect distant information in the conversation and is often victim of prejudices and hallucinations, generating plausible but not always right answers, especially when the data provided by the user are incorrect (Lin & Zhang, 2023; Paul et al., 2023). Moreover, many people are still sceptical about the quality and transparency of the information (how this tool generates recommendations) (Ali et al., 2023; Wong et al., 2023; Gupta & Mukherjee, 2024). Finally, as already mentioned for AI in general, privacy and data protection are factors that reduce the likelihood of using ChatGPT and GenAI, even when the consumer recognizes their usefulness (Abou-Shouk et al., 2024; Niu & Mvondo, 2023; Paul et al., 2023; Wong et al., 2023; Dwivedi et al., 2023).

After an examination of the most important AI-driven recommendation systems most developed in the contemporary economy, highlighting the strengths and weaknesses of each, the next step is to understand if, and in which contexts, these means are more effective in giving purchase advice to consumers compared to human sources.

### 1.4. Human vs. AI-Based Product Recommendations

After analysing human-based and AI-based product recommendations separately, this section makes a direct comparison between the two, highlighting their respective advantages, limitations, and effectiveness in different decision-making contexts. Several studies have directly contrasted human and AI-generated advice, providing valuable insights into when and why consumers prefer one over the other.

The first determining variable is the context or the product that is the object of the choice. On average, people prefer the advice of AI in utilitarian contexts, that is, for logical and analytical decisions (Dietvorst & Bharti, 2020; Osborne & Bailey, 2025; Ramrath et al., 2024), while they prefer human judgement in hedonic contexts, that is, for more emotional and subjective tasks (Longoni & Cian, 2020; Glikson & Woolley, 2020; Xie et al., 2022; Wien & Peluso, 2022; Castelo et al., 2019; Ruan & Mezei, 2022). The underlying reason is that people perceive AI as rational and capable of analysis, therefore more suitable for evaluating products with objective and measurable features (Xie et al., 2022; Xu et al., 2024).

Furthermore, individuals generally see humans as entities with autonomous goals and intentions, while they consider AI as executors of instructions without their own purposes. This is why AI tools are often perceived as more appropriate when they focus on practical and operational aspects, rather than on abstract concepts (Kim & Duhachek, 2020). However, according to the Wien & Peluso study (2022), even for utilitarian contexts there is no preference towards AI recommendations. Since the information is factual and objective, there is no significant difference in the type of recommender. Furthermore, the low empathy and high social distance perceived with these instruments do not seem to have a great relevance in choosing one source over another, which is instead the case within hedonistic contexts.

According to Dietvorst & Bharti (2020), the reason why people more readily accept AI suggestions in deterministic contexts is because human beings unconsciously favour the source of information they believe is most likely to provide a perfect answer. Said that, AI is favoured for objective questions (e.g. mathematical calculations) because there is a high probability of receiving a perfect answer compared to uncertain ones (e.g. medical prognosis), where there is more variability in the accuracy of responses. In the latter, despite a worse average performance, human advice seems to come close to the perfect answer more times than AI, being chosen more often (Dietvorst & Bharti, 2020).

As mentioned before, trust in AI is lower when the task is perceived as subjective rather than objective, even when the algorithms offer superior performance (Longoni & Cian, 2020; Castelo et al., 2019; Osborne & Bailey, 2025). However, increasing the perception of objectivity of the task, or making artificial intelligence more like humans from an emotional point of view, can increase trust and therefore the perceived usefulness of AI (Castelo et al., 2019).

Numerical accuracy also significantly increases trust in AI, and with it the propensity to follow its advice (Kim et al., 2021). However, consumers react more positively when AI provides numerically precise recommendations for utilitarian contexts and vice versa for hedonic contexts. Perfect *"matching"* for consumer trust occurs when the AI gives numerically precise advice in utilitarian contexts and when humans give numerically less precise recommendations in hedonic contexts (Zhu et al., 2023).

Like the contrast between utilitarian and hedonic, also the difference between *low-involvement* and *high-involvement* contexts seems crucial when choosing the source of information: a meta-analysis on the subject showed that people tend to prefer human advice in highly emotional involving settings. This preference shifts to AI in more distant situations, such as future decisions, choices that affect other people, or characterized by little relevance (Jin et al., 2025).

From an interesting study conducted on ChatGPT emerged that people prefer to rely on human recommendations on personal matters such as relationships and personal development, even when this tool provides better answers. Only in one sector, technology and software, people preferred advice from AI. However, when the advisor was an AI and the participants didn't know, the recommendation was perceived as more effective and having a higher quality than the human-led one. This implies that the discrimination against AI-provided recommendations stems only from knowing where they come from, rather than from the actual quality of the advice (Osborne & Bailey, 2025).

In the context of online shopping, generative chatbots are particularly preferred to human frontline employees for products with functional attributes because they provide faster and more accurate information, reducing waiting time and increasing customer satisfaction. The perceived quality of information is similar between AI and human frontline employees, but the efficiency of AI brings a competitive advantage. Instead, when the product has experiential characteristics, customers prefer to interact with a human (Ruan & Mezei, 2022).

Concerning the customer service, much research has shown that although chatbots are useful and responsive for simple tasks (e.g. returns, exchanges and product questions), for more complex issues, some customers still prefer to interact with human assistants (Chung et al., 2018). Similarly, the consumer's level of confidence at the time of purchase has an impact on the acceptance of AI. When consumers already know what they want, they find chatbots more effective and are more likely to use them. If their needs are uncertain, consumers prefer to interact with a human assistant (Zhu et al., 2022). These scientific studies offer further proofs that AI is preferred in deterministic contexts, and regarding choices that can be automated minimizing errors and in which there are fewer variables that generate "uncertainty" in the mind of the consumer.

In the case of wide selection of products, ChatGPT can drastically reduce the negative effects of the *paradox of choice.* However, the preference leans towards human advice when there are few options available (Kim et al., 2023a). On one hand, the greater *"computational capacity"* of GenAI is preferred when there are many choices, which are more difficult for a human to process. On the contrary, human recommendations are preferred when there are fewer choices, when experience in the sector and a touch of subjectivity is sufficient.

In addition to the context and the type of choice to be made, it is very important to analyse the most relevant psychological mechanisms that consumers face when they interface with these new technologies, and above all the impact that these dynamics have on their decisions. In many studies, it has been proven that there often seems to be an almost unmotivated preference for human advice, even when AI clearly offers better performance and advice. This happens mostly, as said before, in tasks perceived as subjective and experiential, for which there is a need for that pinch of intuition and *"humanity"* that AI still doesn't seem to have mastered. Regardless of the validity of this *"human superiority"* within hedonistic contexts, there are unconscious reasons why humans tend to trust their fellow humans more.

The psychological phenomenon behind this preference is called *"human black-box effect"*, i.e. the illusion that humans understand human decision-making better than algorithmic decision-making, even though both are *"black boxes"*. People project their own decision-making logic into other human beings more easily than into algorithms, which increases the perceived understanding of their decision-making process (Bonezzi et al., 2022). Humans *"see more"* in themselves rather than Artificial Agents and this illusion of understanding reinforces trust in human decisions over algorithmic ones, even when these produce more accurate results (Bonezzi et al., 2022). That's why many users ask for greater transparency in algorithmic outputs: they perceive they don't really understand them and don't realize how they reach certain conclusions. A study testified to this underlying lack of trust on AI and found that when the advice to use an AI comes from another human, the intention to use it increases. As a matter of fact, social proof seems to have a significant impact on the likelihood of using an algorithm, which in turn reduces the cognitive load associated with the decision to be made (Gursoy et al., 2019),

Also, it has even been proven that, given the same error, people are more forgiving towards other humans than AI and tend to lose confidence in it more easily (Dietvorst et al., 2014; Glikson & Wooley, 2020). As a matter of fact, according to the research conducted by Dietvorst et al., (2024), people who had seen an algorithm make a mistake were less likely to choose it, even if they knew it was more accurate than a human being. This effect is called *"algorithm aversion"* and seems to be related to the assumption and belief that algorithms are perfect, and not to a lack of understanding of the response. So, when some people discover that these tools can make mistakes, this leads them to automatically reject them rather than accept them with their flaws, as one would do with a human being. Most people are not very forgiving and easily lose confidence in these tools. On the other hand, as noted earlier, in other cases the denial of this tool stems exclusively from prejudice about its reliability (Osborne & Bailey, 2025).

However, there is an opposing strand of literature that instead demonstrates how there are unconscious psychological dynamics that make people more inclined towards algorithmic advice, sometimes in a reckless manner. Although algorithms are often considered black boxes, many people still consider them more reliable than human judgment. A study by Logg et al., (2019) found that when people believe that advice comes from an AI, they trust it more. However, people who are experts in a particular field tend to trust algorithms less on average, making worse decisions. These discoveries have highlighted the relevance of the person's level of competence in choosing the source of advice, but also that AI represents a strong ally in many decision-making contexts, leading to better decisions on average.

More and more people blindly trust the advice of AI, even when better alternatives are available. The phenomenon is largely driven by the belief that algorithms have more skills and are more intelligent than humans, leading them to make better decisions (Paul et al., 2023; Hermann & Puntoni, 2024; Logg et al., 2019). An excess of this attitude leads to the phenomenon of *algorithm-overdependence,* which represents the diametrically opposite situation to that seen before. This is not a positive way of thinking, because although this tool is useful and versatile, it is not yet infallible. It can make people negligent and lead to not monitor the validity and reliability of the results, making wrong choices or spreading misinformation (Alexander et al., 2018).

There is evidence that tourists show less sensitivity to price when travel plans are recommended by AI. Compared to artificial intelligence, tourists believe they better understand the decisions of a human being and, consequently, they examine the price more critically and are more sensitive to it. The underlying reason is that many people believe it is useless to analyse an artificial intelligence analysis in greater depth, because they would most likely not understand it, due to the enormous amount of data through which it provides its outputs. Furthermore, they trust AI more because they perceive it as more objective and less motivated by personal interests than humans (Xu et al., 2024). This study is interesting because it has shown that the human black-box effect does not always have the effect of making people lean towards human advice. On the contrary, a feeling of incomprehensibility of AI makes it even more trustworthy, as it is perceived as a calculation tool of a qualitatively higher level compared to the human brain.

In conclusion, the perceived usefulness of advice from human and AI sources is closely related to psychological dynamics and the specific purchasing context, making the final behavioural response dependent on a multitude of factors. Based on the literature review, there seems to be a strong propensity to follow AI advice in utilitarian purchasing decisions, where rationality, numerical accuracy, and response speed play a key role in evaluating the effectiveness of an information source. Conversely, in more hedonistic and subjective contexts, where emotional and experiential nuances are fundamental, human judgment is preferred. In addition, the level of confidence experienced during a buying situation is an equally determining variable in choosing one source over another. On average, the opinions of others are favoured in situations of greater uncertainty. As for psychological phenomena, *algorithm-aversion* and the *black-box effect* subconsciously tip the balance toward human recommendations, even in situations where AI is clearly more accurate, leading to worse decisions. Conversely, specular approaches such as *algorithm-overdependence* show that a lack of monitoring of AI results, taking its accuracy for granted, can lead to the same outcome.

### 1.5. Research Gap

The first chapter of this thesis has provided a comprehensive overview of product recommendations, tracing their evolution from traditional human-driven influences to AI-led recommendation systems. By examining both historical and contemporary perspectives, this chapter has highlighted the increasing complexity of consumer decision-making and the role of the mentioned information sources in guiding consumers in the context of purchase decisions.

The in-depth review of existing literature regarding product recommendations has allowed to understand the current state of research on this topic, and to individually extrapolate the strengths and weaknesses of the most common sources of advice in modern society. The main characteristics of the sources analysed are listed below:

- Recommendations from friends and family are perceived as very trustworthy thanks to the emotional bond and shared interests with the interlocutor and they are also very personalised. However, they have limited variety and accessibility as they originate from individual experiences, and they may not be entirely accurate and consider new products or trends.
- Traditional word of mouth (WOM) is universally seen as a highly authentic information source due to its spontaneous and non-commercial nature. However, it suffers the same disadvantages as the previous category.
- Electronic word of mouth (e-WOM) provides consumers with a huge amount of detailed and always accessible information. Moreover, these reviews are mainly perceived as genuine as they are generally intended to inform other consumers and help them make prudent purchasing choices. However, the vastness of these data can lead to decision fatigue and expose consumers to fake or inaccurate news.
- Finally, social media marketing and influencer marketing often generate high engagement thanks to the emotional involvement and the parasocial relationship that is created with these figures.

Anyway, it is frequently perceived as ungenuine and less preferred in the context of high-involvement purchases.

As for human sources of recommendation overall, the picture is very nuanced, and no one source stands out above the others. Each has its pros and cons, and they appear to be useful in different contexts and for various products.

Considering trust in the advisor, family and friends are obviously at the top of the list. However, as mentioned above, these types of recommendations generally present some disadvantages, including the low level of variety, availability and possibility to analyse their accuracy. Overall, e-WOM seems to be the best option: it is accessible to everyone 24/7, it has a massive amount of information that can be compared with each other, and it is generally considered genuine and authentic, as it comes from other consumers.

Despite the potential for manipulation, the enormous number of reviews and information available enables consumers to filter contents and autonomously identify the most credible sources.

On the other hand, in the AI domain, leaving aside the many defects that this medium still has today, according to the papers analysed, Generative AI, and more specifically ChatGPT, stand out as the most advanced and powerful recommendation tools developed so far. Unlike traditional recommendation systems that rely on past user behaviour and collaborative filtering, ChatGPT provides real-time, context-aware and personalized product advice, simulating an expert consultant rather than a simple recommender. Studies suggest that ChatGPT-based recommendations enhance decision-making by offering extensive product insights, improving personalization, and reducing choice overload, making it a promising tool for modern consumers navigating an increasingly complex digital marketplace.

That said, to determine the best source of recommendations, a study is needed that puts into direct comparison e-WOM, which seems to be the most complete among the human-based sources, and Generative AI, which differentiate itself from other Artificial Intelligence technologies due to its greater intelligence, perception of usefulness, precision, personalization of responses and many other advantages. In the current literature, based on the careful review that has been conducted, there is a lack of research comparing the effectiveness of e-WOM and GenAI in generating useful purchasing advice for consumers.

More specifically, the conceptual model of this research includes the information source (online reviews vs. ChatGPT recommendations) as independent variable and purchase intention as dependent variable. Concerning the mediator, past research comparing human vs. AI product recommendations analysed the effect of product type, trust, decision complexity, attitude toward AI and many other variables. An interesting mediator for this specific research could be the perception of risk, as this is a factor of utmost importance when interfacing with information found on the Internet and especially when interacting with an artificial intelligence such as ChatGPT. This variable has been included in many study frameworks analysed in the literature review conducted within this chapter, and its close correlation with the source of information and purchase intention is widely documented and proven.

More specifically, advice from *close ties* (family and friends) appears to significantly decrease the consumer's perceived level of risk, which in turn increases purchase intention. This is because of the low perceived social distance and the strength of the emotional bond with these figures, which instils a sense of security in the consumer (Zirena-Bejarano & Zirena, 2024; Kirmani & Ferraro, 2017; Bearden & Etzel, 1982; Haq et al., 2024). Likewise, several studies have shown that e-WOM and online reviews can have the same effect on the mediator variable, further facilitating or motivating the purchase decision. (Chen et al., 2015; Kour et al., 2024; Kirmani & Ferraro, 2017; Sharma et al., 2011; Zhu et al., 2012; Fu et al., 2020; Yang, 2022).

On the other hand, the impact of this variable has not been extensively investigated within the field of the AI recommendations, showing an evident research gap. On these grounds, this research aims to compare online reviews and advice offered by generative AI. This could represent an opportunity to understand which of the two sources is more useful in reducing the feeling of risk during the costumer journey and consequently increasing the intention to purchase. This represents a particularly innovative research aim, as it aims to understand the current feeling of risk and discomfort experienced by the average current consumer when interacting with these cutting-edge tools, and what effect this sensation has on their intention to buy the recommended products.

Particularly, this study will focus on a specific product sector, that of consumer electronics. The confrontation of these two information sources is particularly relevant due to the significative decision-making complexity, the high perceived risk and the strong demand for technical information present in the context of this product category. Also, these characteristics are close to the field of artificial intelligence, making it particularly appropriate for the type of research to be carried out.

Indeed, electronic products fall within the so-called utilitarian purchasing contexts, which have already been extensively analysed by numerous studies, as seen earlier in this study, to compare the effectiveness of human and artificial information sources in stimulating consumer purchases. The following chapter will aim to analyse further papers related to this topic on which to base the research hypotheses. Finally, the present research will offer a new and unique perspective on the comparison between human-based and artificial-based suggestions, confirming or offering new research insights from the current literature.

### 1.5.1 Research Question

Considering what has been said and the research gap found, the research question could be formulated as follows:

*RQ: Does perceived risk mediate the relationship between the source of information (online reviews vs. ChatGPT recommendations) and purchase intention in the electronics sector?*

# Chapter 2 - Theoretical background

According to the literature review previously conducted, e-WOM and recommendations produced by Generative AI are the most effective information sources in stimulating consumers' purchase intention, in their domains (human-based and AI-based recommendations respectively). Said that, the purpose of this chapter is to go deeper into this comparison, and to understand if there is one source that is more useful than another in impacting the dependent variable.

For this purpose, the research section of this chapter will be divided into three paragraphs, the first two of which will focus on the different research questions emerging from the identified literature gap. The last paragraph will be shorter and will not contain an analysis of past studies, but only a representation and commentary on the proposed conceptual model. More specifically:

- The first section aims to explore the state of the art of current literature regarding the effectiveness of these recommendation sources in increasing consumer purchase intention. In this first phase, therefore, the mediating role played by perceived risk will not be analysed, but only the direct correlation between the two manipulations of the independent variable (first online consumer reviews, then GenAI recommendations) on the dependent variable (H1). The main studies conducted specifically on this topic will be cited and, at the end, a research hypothesis will be formulated regarding the superiority of one source of information over the other. This statement will reflect and summarize what emerges from the current literature and, if verified by the experimental study, will represent a significant contribution to scientific knowledge on the subject.

- The second paragraph aims to analyse the indirect effect of the proposed mediation model, carried out by perceived risk and composed of hypotheses H1 and H2. Therefore, the main purpose of this section is to understand the individual effect that the two manipulations of the independent variable (e-WOM vs. recommendations generated by GenAI) have on the mediating variable and subsequently evaluate the final impact of the latter on the dependent variable, i.e., purchase intention. So, this section presents two different research objectives relating to the two different relationships that make up the indirect effect.

  After analysing the main papers on the topic, the hypotheses relating to this part of the conceptual model will be stated: H2, H2, which will hypothesize a preference for one source over another as a means of reducing the consumer's perceived risk, and H3, which will instead focus on the effect of perceived risk on purchase intention. This second research aim will be easier to demonstrate because the relationship between these two variables has been extensively documented in previous academic research.

- In the third and final paragraph of the chapter, the conceptual framework of this research will be shown and commented on, which will graphically represent the theoretical results that came out from the two previous sections.

## 2.1. Literature review

### 2.1.1. The Influence of Information Source (Online reviews vs. GenAI-generated Product Recommendations) on Purchase Intention

Before examining the literature regarding the first relationship of the conceptual framework, it is appropriate to define and conceptualize the dependent variable, i.e. purchase intention. The same procedure will be followed for the other variables that comprise the model, particularly the conceptualization of the mediator and the two manipulations of the independent variable, which will, however, be devoted greater attention. On the contrary, since purchase intention is a variable that has been extensively studied by academic research and represents a factor of intuitive comprehensibility, only its most important characteristics will be discussed.

According to the conceptualization provided by Kim & Ko (2010), purchase intention represents the *"consumer's possibility of purchasing in the future"* (p.167). Likewise, Spears & Singh (2004) define it as the *"intention of consumers to consciously plan or strive to purchase brand products"* (p.54). It is a multidimensional variable and is the result of numerous motivational factors that drive consumers to take an interest in a particular product (Ventre & Kolbe, 2020). As it is intrinsically linked to actual consumer behaviour and therefore to sales, it is a crucial factor for companies to monitor (Kim & Ko, 2010).

As mentioned above, since Generative AI is a very recent technology and therefore still largely unexplored from an academic perspective, the only two studies in the literature that directly compare online reviews with GenAI recommendations are those by Choi et al. (2024) and Christensen et al. (2025), both conducted in the tourism sector, which is by far the most analysed area of research in the literature with regard to ChatGPT product-related recommendations.

Due to this considerable gap in research, which the present study aims to fill, this section will not cite articles that have conducted scientific studies directly comparing these two sources of information (except for those mentioned above). Instead, research that has studied the individual effects of the two manipulations on the dependent variable will be analysed. At the end of the chapter, conclusions will be drawn based on what has been extrapolated from the papers examined.

Beginning the analysis of the literature on the effectiveness of e-WOM on purchase intention, it is first necessary to define and contextualize this variable, providing a historical overview that testifies to the extreme usefulness of this tool for today's consumers.

According to a definition universally shared in literature, Electronic Word-of-Mouth (e-WOM) is defined as *"any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet"* (Hennig-Thurau et al., 2004, p.39). This phenomenon occurs in any digital environment where consumers can share, read or exchange opinions and reviews on products or services. Specific categories of Internet channels exist where this phenomenon is particularly prevalent and useful to consumers.

- *E-commerce websites*: users who have previously purchased products from a specific site provide textual and/or numerical reviews (e.g. from 1 to 10). Basic examples of this category are Amazon, eBay and Zalando.
- *Specialised platforms*: these are applications or websites created with the specific purpose of making consumer-to-consumer reviews accessible via the Internet. They therefore offer users the opportunity to obtain detailed information before buying a product or service. Respectively TripAdvisor for travel experiences (e.g. hotels, flights and tourist attractions) and The Fork for restaurants constitute examples of such platforms.
- *Social media*: including Instagram, Facebook, TikTok and X (ex. Twitter), these channels have grown significantly in recent years and represent a powerful means by which e-WOM spreads today. On these platforms, users from all over the world can exchange opinions in real time directly under posts or videos related to the products in question.

More specifically, based on a trend observed in recent years, in some sectors of the consumer economy, social networks (in particular YouTube, Instagram, and TikTok) appear to be becoming the main vehicles of information between consumers, especially for certain categories of products, such as experiential products (travel, restaurants, etc.). In fact, thanks to features such as the immediacy and usability of content, they are surpassing, in the eyes of consumers, the perceived usefulness of the platforms typically used for these purposes.

This phenomenon happened because social networks have radically changed the way consumers interact with brands. These tools are not just advertising platforms that companies can exploit, but interactive spaces where consumers co-create meanings and content. All these platforms allow the creation of communities that foster loyalty, involvement and a sense of belonging to the brand (Pütter, 2017). For these reasons, *user-generated content* (UGC) on these platforms is becoming increasingly influential, even compared to content generated by companies in terms of credibility and impact.

- *Forums and communities*: e.g. Quora and Reddit, these are more niche platforms, generally used to seek information on more specific and complex products than those normally addressed on other platforms. However, because these are smaller communities, the perceived greater authenticity of reviews often stimulates greater purchase intent than traditional media (Zhu et al., 2012; Fu et al., 2020).

Scientific research on e-WOM exploded after 2010, with an exponential increase in publications. Among the main thematic clusters analysed are the effect of e-WOM on consumer trust, attitude, and behavioural outcomes, and the characteristics of reviews most valued by Internet users (Donthu et al., 2021).

Such as traditional WOM, e-WOM offers the possibility of obtaining unbiased product information from other consumers. It is in fact a spontaneous and organic mean, where satisfied consumers act as informal promoters of the products and brands they have purchased (Sulthana & Vasantha, 2019). However, taking place on the Internet, it is much more immediate, accessible and rich in information than the previous one, which is based on face-to-face interactions.

E-WOM has hugely different effects on consumer behaviour depending on the culture of Internet users, and several cross-cultural research has testified to this peculiarity. For example, based on research by Christodoulides et al., (2012), it seems that British consumers are very much victims of *negativity bias* (they are very susceptible to negative reviews), while Chinese consumers are more influenced by recency. Another interesting cross-cultural study analysed two quite different countries, namely Spain (a developed and individualistic culture) and Colombia (an emerging and collectivist culture), has shown that the intention to purchase is influenced by different psychological and cultural factors depending on the country. In the first one, functional and cognitive factors (perceived usefulness and ease of use) play a key role in the purchasing process, while in the second, emotional and psychological factors such as perceived behavioural control, buying impulse and self-efficacy prevail (Peña-García et al., 2020).

In the earlier chapter of this research (section 1.2.3.) has been demonstrated and deepened the usefulness of e-WOM in helping consumers search for information and make more informed purchasing decisions. In fact, several studies have shown the significant role of online content and reviews in increasing consumers' purchase intentions. This occurs directly or indirectly thanks to certain predominant factors, which will be analysed in greater depth in this section.

Firstly, the positive valence of reviews has found to be one of the most important drivers influencing consumer attitudes and behavioural intentions. For example, Haq et al., (2024), demonstrated that this variable enhances consumers' purchase intention through the mediated effect of attitude toward the brand and perception of brand quality. In addition to the positive valence of the message, the credibility of the information, i.e. the belief of reliability and accuracy, and the attitude towards e-WOM are critical variables in enhancing consumers' purchase intention (Kour et al., 2024).

The dual role of valence and credibility in influencing the dependent variable is even more impactful in social media contexts, where relational closeness is a primary variant. It seems that e-WOM within these platforms, especially those characterized by strong-ties (e.g. Facebook, Telegram), increases purchase intention through the mediated effect of the shorter psychological distance and higher perceived value of reviews. E-WOM with a contrasting meaning, on the other hand, decrease the dependent variable due to the greater perceived cognitive effort (Yang, 2022). These findings are completely in line with those of Gunawan & Huarng, (2015), who testify that the source credibility and normative influence typically present in these contexts can greatly alleviate the negative effect exerted by the consumer's perceived risk and consequently increase purchase intention.

According to a study by Fu et al. (2020), besides the *normative influence* (conforming to be socially accepted), the *informational influence* (getting information from others to understand what is correct) resulting from product recommendations on social networks is equally important, and both have a greater impact than the perceived quality of information in increasing the intention to purchase online. This relationship is even more pronounced in the case of *low involvement products,* for which consumers rely more on *heuristics,* i.e. unconscious mental shortcuts used to make decisions that are considered less important by spending as few cognitive resources as possible. The impact of these two types of influences is also inferred from the paper by Park et al., (2007), according to which in the case of *high-involvement* products, both quantity (normative influence, acts on the *peripheral route*) and quality (informational influence, acts on the *central route*) of the reviews are found to be crucial in increasing intention to buy.

A study by Filieri (2014) provides further confirmation that both informational influences (quality and credibility of the information) and normative influences (product ranking and review score) are complementary and equally relevant in increasing the propensity to adopt the information. However, Chen et al., (2015) found that consumers with *low susceptibility to information influence* tend to seek information from multiple sources (including the manufacturer's website) to obtain a more complete picture of the product. According to Yoon (2012), the perceived effectiveness of online reviews is radically accentuated when there is a match between the level of involvement of the review and the product: the more the product is involving (for example, a camera), the more the information must be rich and detailed (for example filled with images) to generate the adoption of the information by the consumer.

In the context of online reviews of services (e.g., in the tourism sector), characteristics such as duality of the review (highlighting both positive and negative aspects), the perceived competence of the reviewer, and homophily (similarity between user and reviewer) are also highly relevant in influencing purchase intention (Onofrei et al., 2021). These findings are aligned with those of Roy et al., (2018), who found that mixed-valence reviews are generally considered more credible and effective, as they offer a more balanced picture of the product. According to Filieri et al., (2018), these variables improve the purchase intention both directly and indirectly through the perceived helpfulness of the information.

The perceived usefulness of reviews is also a crucial variable that mediates the relationship between several e-WOM features and purchase intention, and its role is highlighted in articles written by Erkan and Evans (2016) and Ventre and Kolbe (2020). The former emphasizes the importance of the close relationship between this variable and the individual consumer's need for information, while the latter emphasize the parallel but also complementary role of trust in influencing this variable.

One of the most frequently cited and used models to explain how the peculiar elements of e-WOM act on behavioural outcomes is the *Elaboration Likelihood Model* (ELM). A massive meta-analysis carried out by Ismagilova et al., (2019), shows that the purchase intention is an extremely multifaceted variable, so this dual-route processing approach is extremely well-chosen. According to the authors, trust, quality of reviews, and perceived usefulness are the main predictors of the dependent variable. The same theoretical model was adopted and extended by Majumder et al., (2022), who showed that both variables acting on the *peripheral route* (rating and length of the review) and those acting on the *central route* (content of the review) have a positive effect on the perceived usefulness of the information, in line with many previously mentioned studies.

Furthermore, by extending the ELM to the product category, it emerged that *central cues* have a stronger impact on experiential products (e.g. videogames) while *peripheral cues* are more important in the contexts of search goods (e.g. food). These insights are consistent with an earlier paper written by Filieri & McLeay (2014), which showed that both the added value of the information (*central route*) and the average product ratings (*peripheral route*), represent additional factors that can increase intention to buy, in different ways depending on the context. In addition, a study on Douyin (the Chinese TikTok), a short-video platform, has shown that social signals (likes and comments) increase the likelihood of impulse buying, as they act on the *peripheral route*. As seen in other research, this effect is particularly pronounced for *low-involvement* products compared to *high-involvement products*. The latter, in fact, use the *central route* of the brain, which is linked to rational decisions guided by the quality and consistency of information (Huang et al., 2025).

In the context of peer communication on social media, the strength of ties and identification with the peer group are positively correlated with purchase intention, through the mediated effect of product involvement and product attitude. The entire process is also affected by the moderating variable need for uniqueness, which determines how much an individual is willing to let himself be influenced by the group (Wang et al., 2012). In addition, in the context of viral marketing via e-mail, it seems that e-WOM communications initiated by strong ties are highly effective in capturing attention and generating product awareness. On the other hand, counter-intuitively, the conversion phase is more influenced by weak ties or ones characterized by demographic dissimilarity (De Bruyn & Lilien, 2008). This is the concept of the *"strength of weak ties"*, which according to Granovetter (1973), are more useful for conversion than awareness in the context of consumer decisions. These external social cues (reviews, ratings and comments left by other users), according to Xiao et al., (2019), work particularly well when the perceived risk is high and when there is a low level of familiarity with the brand. Leveraging the *Cue Utilization Theory*, this paper showed that according to consumers who rely on external (non-intrinsic) cues to evaluate products online, social reviews emerged as the most influential drivers of purchase intention, through the interplay of a higher perceived functional and emotional value.

The perceived credibility of reviews is also a topic covered in the papers by Zangeneh et al. (2014) and Ali & Cai (2022), which show, respectively, that reviewer perceived expertise and review quality are crucial precursors of this factor, which in turn has great impact on behavioural intention. In the context of online food purchases in China, the credibility of e-WOM (evaluated according to 4 dimensions, namely expertness, trustworthiness, objectivity, homophily) significantly lowered the level of perceived risk, which in turn increased the willingness to adopt the information through the effect of argument quality and information usefulness (Hussain et al., 2017).

In a particularly important meta-analysis on the subject, the main predictive factors of e-WOM characteristics on sales were analysed. Although the variable under study is not purchase intention, these two elements are extremely correlated and consequential to each other. Volume, positive valence and a moderate level of variance (both positive and negative) of the reviews reconfirmed their dominance in consumer decisions, being the strongest drivers of sales (Rosario et al., 2016). Leong et al., (2021) adds that also relevance and *information task-fit* (how much the information satisfies the user's specific information need) significantly increase the intention to purchase on social media through a greater likelihood of information adoption. Baitaneh (2015) found comparable results in the context of university enrolment: credibility, quantity and quality of online reviews regarding a specific institution significantly increase the intention to purchase (i.e. to enrol in that university), both directly and indirectly via brand image.

The previous findings resonate particularly with the content of a study on consumers from the United Arab Emirates (UAE), which has shown that e-WOM enhances purchase intention both directly and indirectly through the mediation of brand image (Nuseir, 2019). Another study carried out in the same area showed that the intention to purchase is influenced by both the intrinsic characteristics of the review and the website. The former includes the consistency, quantity, recency and average rating of the review, and the latter include the popularity of the site, its perceived reliability and its degree of internationalization (Almana & Mirza, 2013). The validity of this conceptual framework was also confirmed by Jalilvand & Samiei (2012) in research concerning the automotive sector in Iran.

Many studies have also analysed the role of brand equity in mediating the relationship between online consumers' interactions and their buying attitudes. An e-WOM analysis on social media has shown that consumer-to-consumer online communication influences purchase intention only indirectly, through the mediated effect of brand equity (Poturak & Softić, 2019). This interesting study shows that often simple word of mouth is not enough, but consumers need to perceive the value of the brand. This finding aligns perfectly with those of Chakraborty & Bhat, (2017) who have examined electronic products market in India. According to this paper, credibility of online reviews increases the intention to purchase through five different dimensions of brand equity: brand awareness, perceived value, brand personality, organizational associations and perceived quality. This model, theorized by Aaker (1991), was used by the author a second time to perform an analysis on the same consumer sector in India, taking into account user interactions on Facebook. This study showed that brand awareness and perceived value are significant mediators of the relationship between the credibility of online reviews and purchase intention (Chakraborty, 2019).

Kudeshia and Kumar (2017) and Prasad et al. (2019) also reinforce the idea of the mediating function of the brand between electronic word-of-mouth and consumer's intention to buy. Spontaneous communication regarding smartphone brands amongst consumers on Facebook has found to have a noteworthy influence on purchase intention, through the effect of brand attitude (Kudeshia & Kumar, 2017). Likewise, research on Generation Y has discovered that e-WOM and social media usage influence purchase intention both directly and through the interplay of so-called *conviction*, which is a form of deep, stable and progressive trust that a consumer develops over time towards a brand or an online platform, based on repeated and consistent experiences of satisfaction, reliability and transparency (Prasad et al., 2019).

Zhu et al. (2020) and Wang & Chang (2013) operationalized and further demonstrated the validity of these relationships using the *Stimulus-Organism-Response* (SOR) model. Respectively, social presence and interactions from strong ties (stimulus), were significant in increasing trust and *perceived diagnosticity of the information* (organism) which in turn increased final costumer intention to purchase (response).

Various psychological mechanisms also contribute to the multidimensionality of consumers' final behaviour. A study by Huang et al., (2019) showed that the tactile cues contained in online reviews increase the intention to buy through the mental simulation that takes place in the consumer's mind when exposed to this sensory content. Moreover, according to *Regulatory Focus Theory*, *promotion-focused* consumers seek gains, being more sensitive to positive reviews, while *prevention-focused* consumers avoid losses, and are therefore more susceptible to negative reviews. In this regard, according to Hsu et al., (2016), *regulatory fit* (consistency between the valence of the review and the consumer's motivational orientation) significantly increases the intention to purchase. It seems that this is especially true for search products, since consumers trust the reviews of these products a lot when making their choices.

Another determining factor in influencing the effectiveness of e-WOM on purchase intention is certainly represented by information overload. According to Furner & Zinko, (2016), it appears that the effect of this variable on purchase intention follows the shape of an inverted U, showing high values in the presence of a moderate amount of information, and low values in more extreme situations, especially when searching from a mobile device, which is generally more difficult to use. Park & Lee (2008) also showed that this effect is particularly pronounced when the reviews are technical and detailed and when it comes to products characterised by high involvement.

The informativeness of online reviews is another non-negligible factor when analysing the behavioural output of e-WOM. Cao et al., (2011) used modern text mining techniques and showed that certain linguistic characteristics of reviews, such as length, valence (positive or negative) and recency are the strongest predictors of the perceived usefulness of a review, and thus of purchase intention. Also, Zhang et al., (2014), who used the *Heuristic-Systematic Model*, confirmed that both *heuristic cues*, based on cognitive shortcuts (e.g., source credibility, number of reviews), and *systematic cues*, processed more carefully by consumers (e.g., informativeness and persuasiveness of arguments), significantly enhance purchase intention. Although they use different models, the results of these papers are extremely consistent with those that used ELM as a theoretical framework, namely that both cognitive and more intuitive factors are crucial in increasing purchase intention.

Regarding product category, a widely used classification in the literature analysing the effectiveness of e-WOM on willingness to buy distinguishes between *search products* (e.g., smartphones) and *experiential products* (e.g., hotels). Jiménez & Mendoza (2013) have shown that for the former, systematic cues such as the level of detail in reviews are more important, while for the latter, the level of agreement between reviewers is more important, supporting the *"wisdom of the crowd"* effect. These results are in line with those of Yaylc & Bayram (2012), who demonstrated that in the context of purchasing electronic products, the fundamental characteristics that determine an increase in purchase intentions are consistency, recency, clarity, and review ratings.

Gender also drives consumer responses with respect to online costumer reviews. According to Van Slyke et al., (2022), it seems that men perceive online shopping in a more positive way and are much more inclined to buy online than women. This happen because they have a more functional and practical approach to online shopping, which leads them to consider this tool very advantageous and not overly complex. Women, on the other hand, are on average less familiar with it and tend to see shopping as a social experience, which the online version cannot replicate. In fact, according to a study by Chen & Chang (2018) concerning online reviews on Airbnb, seems that men are more influenced by review scores, showing a more heuristic approach, while women place more importance on the quality of information, interfacing in a more reasoned manner. These findings show that men on average experience online shopping in a more relaxed way than women. These findings resonate with Fan & Miao (2012), who used an extended version of ELM model, showing that low expertise, high involvement and homophily of the consumer significantly increase the intention to purchase thanks to the effect of the greater credibility of e-WOM. However, for men only involvement influences the independent variable, as they appear to be more focused on the functionality of the product rather than the perceived closeness to the author.

Further analysing gender differences, an eye-tracking analysis carried out through a shopping simulation on Taobao showed that people pay more attention to negative reviews and this phenomenon leads to a decrease in the intention to purchase. This is especially true for women, whose perceived risk level rises higher when looking at negative reviews (Chen et al., 2022). The same effect, called *negativity bias,* was found by Bae & Lee (2010) in a study regarding the combined effect of the review's rating and the reader's gender. It was seen that women's purchase intention is more influenced by online reviews (both positive and negative) than men's, and that negative reviews have a greater effect on purchase intention than positive ones.

Huang & Chen (2006) also came to the same conclusions, showing that negative reviews have a greater impact than positive ones in influencing buying intention. Furthermore, according to the results of this study, customer reviews are perceived as more reliable and persuasive than those of experts, although they are considered less competent, demonstrating how the authenticity of e-WOM is a key element of its effectiveness. According to the authors, online reviews generate a *herding effect* (mass imitation), acting as an informative influence for consumers who read them. Likewise, Mauri & Minazzi (2013) have shown that in the context of the hotel sector, host responses to reviews generally have a negative effect as it deprives the e-WOM of a core element of its credibility, i.e. the absence of commercial purposes. Furthermore, according to Reimer & Benkenstein, (2016), when a review is perceived as reliable, the intention to purchase is directly proportional to the valence (positive or negative). On the contrary, when the review is perceived as not reliable, a *boomerang effect* is generated, in which positive reviews decrease the intention to purchase and vice versa. This happens because of the mediated effect of the so-called *reactive behaviour*: the user perceives an attempt at persuasion and reacts by opposing it and behaving in the opposite way (Reimer & Benkenstein, 2016).

The attitude toward a specific review platform also has its relevance in this context. Hajli et al., (2017) has shown that trust in Facebook increases the active search for user-generated contents, which in turn increases the willingness to buy thanks to the greater familiarity with the platform and social presence. Research on the same social network employed the *Technology Acceptance Model* (TAM) to demonstrate the efficiency of this platform as a tool to support consumer choices. It was found that ease of use increases purchase intention through perceived usefulness and attitude, with a positive moderating effect of perceived enjoyment during the process (Di Pietro & Pantano, 2012).

Enough research has been analysed to state that e-WOM is undoubtedly a primary source for consumers seeking information for future purchases. More specifically, as seen, the factors most considered in assessing the effectiveness of online reviews are the valence, credibility and quality of the information provided, which significantly improve behavioural intention both directly and indirectly through several intermediate factors such as perceived credibility, trust and perceived usefulness. In addition to these general dimensions, there are also contextual characteristics such as the type of product (e.g. search or experiential, low or high involvement), consumer characteristics (e.g. gender, culture, cognitive engagement) and contextual elements (platform, source or device used). Finally, psychological mechanisms such as social influence, perceived risk, homophily, and information overload further modulate consumer responses, generating an even more varied and differentiated picture of possible purchase scenarios.

In conclusion, it can be safely affirmed that online reviews are not simply a supporting factor in consumer decision-making, but a crucial information tool that consumers actively rely on to reduce uncertainty, compare alternatives and ultimately justify their purchases. Thanks to its easy and immediate accessibility, breadth of content and sense of authenticity, it is particularly useful to counteract the great complexity and quantity of content in today's digital environments and, ultimately, for increasing consumers' purchase intent.

Having said this, the next research phase concerns the analysis regarding a much more up-to-date information source, namely the Generative AI-driven product recommendations, which undoubtedly represent the most cutting-edge technology for this purpose right now. Several papers will be analysed to understand whether, and to what extent, these emerging technologies replicate, enhance, or disrupt the degree of influence exerted by e-WOM on the dependent variable. Before doing so, the topic will be introduced in general, emphasising the usefulness of this tool in supporting consumers in their purchasing choices, as done before with online reviews.

Artificial Intelligence has dramatically transformed the way consumers gather product information and make purchasing choices (Kim et al., 2023d). In recent years, technological progress in the field of *Natural Language Processing (NLP*) has led to the creation of AI conversational agents capable of understanding and producing language similar to human communication (Paul et al., 2023). In fact, thanks to the advent of *Generative Artificial Intelligence*, and in particular *Large-Language Models (LLMs)*, of which ChatGPT is a part, product recommendation systems have undergone an enormous metamorphosis. These tools have already shown remarkable potential, outperforming by far traditional algorithms in enhancing the user shopping experience (Hermann & Puntoni, 2023).

As a matter of fact, possessing tremendous capabilities in language understanding, reasoning, planning, and generation, these cutting-edge technologies represent a valuable help during the consideration and evaluation phases of the consumer journey, offering more intelligent user-system interactions, enhancing the personalization of content generation, improving data representation (it can generate texts, images and videos as output) and achieving generative item recall and ranking (Wang et al., 2023; Al-Hasan et al., 2024).

As stated in the past chapters of this research, the main problems related to the traditional recommendation systems were the *cold start* (new users or products), the lack of context (mood, seasonality, natural language), the poor explanatory capacity, and the *"black box effect"* that led to a decrease in user trust in the long term (Malikireddy, 2024). Despite everything, these algorithms have been efficiently applied in many fields, such as e-commerce, social networks and streaming platforms. However, compared to these older systems, the main feature of the new GPT-based chatbots is that they can engage in human-like conversations, representing an important opportunity for technological advancement in the field of personalized product recommendations (Al-Hasan et al., 2024).

There is a considerable amount of fresh research that has documented the development of recommendation algorithms based on generative AI. These innovative technologies show great promise and seem to exceed, according to the results, traditional models in terms of accuracy, predictive capability and understanding user intent (Mukande et al., 2024).

As specified before, classical collaborative filtering, used by traditional algorithms, relied only on past interactions and similarities between users, not capturing deeper individual tastes or contextual purposes. Instead, new generative models learn the distribution of user data and generate new realistic recommendations, delivering increased engagement, a higher average order value (AOV), and more effective upselling and cross-selling strategies (Mishra et al., 2025). They are found to have many advantages such as the generation of realistic synthetic data, improved coverage, diversity and personalisation, and the ability to learn hidden structures in data. These are important steps forward compared to traditional systems, which instead presented cold start, *data sparsity and diversity* (repetitive suggestions and minor variation) (Deldjoo et al., 2025; Mishra, 2025; Ayemowa et al., 2024). According to a study by Aggarwal, (2025), due to improved explainability, multimodality, and personalization of recommendations, algorithms based on Generative AI generate +42.5% user trust, +35.8% acceptance of recommendations, +35% overall satisfaction, and +32% conversion rate compared to conventional systems. Furthermore, an integration of ChatGPT with traditional recommendation systems has been shown to generate more personalized, contextual and engaging recommendation messages to stimulate upselling in the hospitality industry. It increased message quality, engagement and conversion rate (Remountakis et al., 2023). Finally, a study conducted by Malikireddy (2024) showed that GenAI-based recommendation systems have a *prediction accuracy* (the system's ability to correctly recommend products that the user is really interested in buying, clicking on or exploring) on average 27% higher than traditional algorithms, with peaks of 29% and 34% respectively for the electronics and fashion sectors.

It should be specified that the recommendation algorithms just discussed do not specifically constitute the object of the present study, which is instead represented by *LLMs* (and in particular ChatGPT), i.e. a specific category of Generative AI with which it is possible to engage in conversation. The mention of these results was only meant to highlight the objective superiority of generative AI over traditional AI, typically defined as *predictive*, in creating useful content for users.

From now on, however, the analysis of the literature will only concern papers dealing with this specific category of AI, and particularly the effectiveness of these tools in affecting consumers' purchasing decisions. This body of research, as already mentioned, will be compared with the analyses just conducted on e-WOM and online reviews, and then a research hypothesis regarding the most effective source of information will be formulated.

It is important to emphasise that the significantly smaller number of sources attesting to the usefulness of this tool compared to those concerning e-WOM can mainly be attributed to the fact that it is a particularly recent technology, which only became widespread among Internet users in the last few years. For this reason, the number of papers thoroughly analysing consumers' habit of obtaining product-related information from ChatGPT or other GenAI chatbots is not considerable, but large enough to draw conclusions regarding its usefulness.

As in the case of e-WOM, the mediating value exerted by perceived usefulness and trust has also been attested for recommendations provided by GPT-based chatbots. Iranmamesh et al. (2024), using both *Technology Acceptance Model* (TAM), which focuses on perceived usefulness and ease of use, and *Elaboration Likelihood Model* (ELM), showed that the accuracy, completeness, and diagnosticity of ChatGPT's responses influence the intention to adopt this tool to obtain information about products and services. Similarly, Silalahi et al., (2024), using the ELM model, observed that the perceived quality of information and perceived usefulness influence trust through deep cognitive processing (*central route*), while anthropomorphism and the quality of interaction strengthen the same variable through emotional and heuristic shortcuts (*peripheral route*). Trust, in turn, as observed in other studies, increases the intention to adopt the information. However, the perceived risk and complexity of information have significantly undermined trust and hindered the adoption of these technologies. In another study on tourism in Egypt using the *Technology Acceptance Model*, it was seen that perceived usefulness, perceived ease of use and attitude toward ChatGPT have a significant effect on intention to use, both directly and indirectly through perceived enjoyment (Abou-Shouk et al., 2025)

On the other hand, research by Gupta & Mukherjee (2024) shows that the adoption of product-related information offered by GenAI is the result of a chain of mediations among: technology readiness (made up of innovativeness and technological anxiety), technology characteristics (split into personalization, anthropomorphism, search experience), information characteristics (authenticity and credibility), *Unified Theory of Acceptance and Use of Technology* (UTAUT) variables (perceived usefulness and ease of use, social influence and facilitating conditions) and finally trust and attitude towards GenAI.

A subsequent study, building on the same theoretical model (UTAUT) and extending it by including the negative moderating effect of trust and technology anxiety, showed that all variables, except social influence and technology anxiety have a direct positive effect on behavioural intention, which is the intention to adopt information provided by ChatGPT. Also, in this model trust acts as a negative moderator, which can be explained as a *substitution effect*: paradoxically, a high level of this variable makes less relevant the impact of psychological and functional elements related to the usefulness of this technology (Foroughi et al., 2024).

Similarly, Pathak et al., (2024) demonstrated that ChatGPT's usage intention for purchase purposes is significantly correlated to its perceived efficiency, which is divided into attitude toward chatbots, AI service quality, perceived anthropomorphising, and the *"feeling of awe"*, i.e. the amazement felt by consumers as a result of the answers given by the GenAI.

Another crucial feature in influencing the adoption of the information provided by these chatbots is also represented by the familiarity of the users about this technology. According to Arce-Urriza et al., (2024) this factor increases the willingness to adopt ChatGPT information both directly and indirectly through perceived usefulness, trust and human-likeness, already mentioned in the previous paper. The only negative mediator, on the other hand, is privacy risk, which as will be seen in the second section of this chapter represents the biggest deterrent and obstacle to the use of these tools. At the same time, prior use experience significantly increases intention to use ChatGPT through a higher perceived ease of use and perceived usefulness. In addition, exposure to positive information on this tool has the same effect, whereas the opposite situation occurs when the user is exposed to errors in responses (Kim et al., 2023c).

The artificial nature of ChatGPT seems to be a significant factor in making it appear to users as an impartial source, free from commercial bias. A study compared the effect of Bing Chat (an algorithm that uses the same technology as ChatGPT) recommendations and traditional AI recommendation systems (Amazon) on the formation of the consumer *consideration set*, i.e. the shortlist of products that a customer considers for purchase. According to the results, the perceived better performance of the new GenAI-based technologies generated a higher intention to adopt the information provided compared to Amazon through a mediated effect of trust in recommender (ChatGPT) and trust in recommended product. According to this model, trust in ChatGPT, seen as a neutral source free from marketing purposes, transfers trust to the suggested products (Chang & Park, 2024).

This emerging technology also appears to be particularly effective in mitigating the effects of choice overload, a common psychological challenge faced by consumers when exposed to many purchasing options. According to Kim et al., (2023a), when the advice comes from ChatGPT, the number of recommended options and purchase intention are positively correlated (contrary to what happens in the case of human recommendation agents, as found in the literature review on e-WOM), through the mediation of perceived information accuracy. However, the same effect has been studied by Shin et al., (2023) for the tourism sector. It has been proven that in the context of choice overload, the reduction of choices made by AI negatively impacts users' visit intention, due to the mediated effect of lower trust and satisfaction. This happens because users on average don't trust ChatGPT when it filters and reduces options on its own, perceiving that they lose control within the selection and purchasing process. This negative effect becomes even more pronounced when the initial number of options is high. Conversely, when the reduction in options is carried out independently or by a trusted peer, the negative impact of product skimming on visit intention is drastically reduced (Shin et al., 2023).

As already pointed out, trust represents a fundamental factor regarding this information source and is a variable closely correlated with the intention to interact with it and adopt the information provided. Ali et al. (2023) and Abou-Shouk et al. (2024) deepened this relationship through the *Affordance-Actualization Theory* to show the usefulness of this tool for obtaining personalized travel recommendations. Ali et al., (2023) demonstrated that the so-called *"affordances"*, which are relevance, credibility, usefulness and intelligence, have a significant positive effect on the intention to use the suggestions provided by ChatGPT through the mediation of trust. Even more interestingly, the same conceptual model, was expanded by introducing the moderating effect of the risk to data privacy and security, which was found to significantly decrease the impact of trust on the adoption of information, more markedly in Omani than in UAE travellers (Abou-Shouk et al., 2024).

The linguistic style employed by ChatGPT, along with the precision in showing numerical results, also have an impact on users' behavioural outcomes. Baek et al., (2025) studied the tourism sector using these tools, and found that for experiential services an informal chatbot language style generates more positive responses, through increased trust, perceived anthropomorphising, and decreased social distance. In contrast, it works best for tourism boards to converse with a formal style, as it is consistent with their role. Similarly, a Korean study on ChatGPT showed that trust on the tool, anthropomorphising and *media richness* (the perceived communicative richness of a message, i.e., how vivid, interactive, and engaging it is through text and images) have a significant positive effect on purchase intention (Kim et al., 2024b). Zhu et al., (2023), have shown that in more utilitarian purchasing contexts, consumers prefer ChatGPT over human advice, especially when it presents answers with high numerical accuracy. When this combination of factors is present, the *matching effect* exponentially increases purchase intention and consumer adoption of the recommendations. These results are in line with those of Kim et al., (2024a), who demonstrated that in the context of tourism, personalized recommendations offered by ChatGPT generate a greater intention to visit than humorous ones. Instead, this relationship is reversed when advice comes from human sources. As evidenced by the findings, the preference for AI over human sources depends on the interplay between linguistic style and the specific consumption context.

The level of psychological closeness perceived with the chatbot during interaction is equally important in determining consumers' response to recommendations provided by ChatGPT. Factors influencing this variable, already examined in the current literature, include parasocial interaction, perceived warmth, and perceived social distance from the algorithm. Doung et al., (2024) have shown that in the tourism sector the first variable significantly enhances continuation usage of ChatGPT, both directly and indirectly through an increased customer satisfaction. Another study conducted in the same field used the *Stimulus-Organism-Response* theoretical model (SOR) to show that both objective utility and external influence are crucial in enhancing the dependent variable. Specifically, the Stimulus, composed of social influence and perceived value, affected the Organism, defined by trust, perceived competence and parasocial interaction. These factors, in turn, positively influenced the final Response, represented by the intention to use ChatGPT for obtaining information (Xu et al., 2024). The same framework was used by Pham et al., (2024) with Vietnamese tourists, revealing that perceived warmth, perceived competence and communication speed significantly increase the continuance usage intention via trust and attitude, while technology anxiety moderates these effects negatively.

Demographic and psychographic factors also influence the willingness to follow advice provided by generative AI. In this regards, Alizadeh & Kashani (2024) note that personalization, accuracy, and convenience of these tools are more influential for women, young users, and those with master's degrees. In the same way, research conducted on Israeli tourists used *Technology Acceptance Model* and found that perceived ease of use impacts the intention to adopt the information received from ChatGPT through the mediation of perceived usefulness and trust. This effect was more pronounced in young individuals than in older people (Solomovich & Abraham, 2024). Kim & Koo (2024), on the same wave, demonstrated that the perceived novelty associated with ChatGPT significantly enhances users' intention to act upon its advice with personal innovativeness positively moderating this relationship.

An interesting study analysed the impact of errors or ethical issues present in ChatGPT's trip planning scenarios. These two factors have greatly diminished the satisfaction and acceptance of the chatbot responses, due to a decline in trust. However, many participants exhibited a behaviour called *"moral decoupling"*, ignoring negative ethical aspects when the output provided was useful and detailed. Interestingly, the presence of obvious errors paradoxically mitigated the effect of negative premises on trust in some participants. This suggests that humans react better when they personally experience ChatGPT's fallibility, compared to when they are exposed to negative news and opinions about the tool (Kim et al., 2023b).

Duwadi & Cautinho (2024) have enriched the literature with a far-sighted study offering valuable marketing perspectives. Their study tested the effectiveness of physical kiosks placed in front of stores, equipped with a ChatGPT-based product recommendation system designed to help and personalize customers' shopping experience. Participants noted ease of use of the interface, accuracy of recommendations, and a naturally interactive purchasing process. As well as providing further evidence regarding the notable usefulness of GenAI within the consumer purchasing process, they also suggested a possible practical application of these tools by companies in their retail stores.

Finally, the last three articles that will be analysed in this section before formulating the research hypotheses are currently the only scientific studies that have compared the effectiveness of these two sources of information in increasing purchase intention. The first was written by Mladenović et al., (2024). While it is not empirical research, this work represents a conceptual exploration of an innovative information tool accessible to all contemporary consumers with Internet access. The paper in fact refers to *synthetic WOM* (syWOM), generated by Generative Artificial Intelligence tools, such as ChatGPT, applied to the travel and hospitality sector (as seen above, this tool has been widely used to the advantage of tourists, but it is potentially useful to consumers interested in any product category), using information contained in other sources and platforms (e-WOM) as input.. According to the authors, it is an enhancement of the traditional WOM and e-WOM due to advanced customisation, massive scalability, real-time interactivity and greater consistency and traceability. In fact, this kind of word of mouth can generate better reviews being useful both in the pre-trip phase, for the search of information, and post-trip for the sharing of experiences useful that will be useful for future tourists.

The second paper was written by Choi et al., (2024), who conducted an experimental investigation to compare these two sources. The purchasing area is still tourism, where e-WOM and recommendations based on Generative AI were compared to test the difference in generating the intention to book Airbnb accommodation. In general, it seems that online reviews generate more intention to stay because of the greater trust. However, it was found that the moderation relationships performed by the accommodation's psychological social distance (near vs. far) and product type (basic vs. deluxe accommodations) paint a more nuanced picture. For near accommodations, e-WOM is perceived as *"socially closer"* as users seek more personal and authentic experiences. Conversely, if the accommodation is far away, ChatGPT's greater versatility and responsiveness is preferred. Following the same logic, for basic accommodations, online customer reviews are preferred as they are more useful in providing reassurance about practical and basic aspects, while ChatGPT works better for more luxurious accommodations thanks to the more objective and professional tone of AI (Choi et al., 2024).

Finally, Christensen et al., (2025), analysed the preference between Generative AI-based recommendations and traditional sources (e.g. TripAdvisor) for Gen Z/Millennials seeking advice for their travel plans. Despite frequent algorithm hallucinations, many consumers in this case preferred ChatGPT recommendations. The main reasons included the perception of greater impartiality, a sense of personalisation and originality, distrust of traditional sources (TripAdvisor and official corporate sites) and the absence of commercial interests.

To summarize the most significant findings of the literature review regarding the usefulness of ChatGPT, as previously done with e-WOM, it is essential to emphasize several advantages of this technology. Among its key strengths there are a high degree of personalization, real-time interactivity, and the perception of impartiality. It would not be an overstatement to say that, at least regarding these three parameters, the utility of GenAI exceeds that of online reviews. Additional undoubted merits include its accuracy, completeness and usefulness in the context of complex decisions or decisions characterized by a high number of options, thanks to its ability to reduce uncertainty and streamline decision processes.

Nonetheless, there are also clear limitations associated with the use of this technology, which will be examined in more detail in the following paragraph of this research. The most prominent deterrent to adoption is the fear for security and the use of personal data, especially in cultural contexts that are more sensitive to privacy and characterized by a low technological maturity. Additional inhibitors are technological anxiety, low familiarity with this tool and the perceived lack of *"relational authenticity"* which may lead to feelings of disorientation and unwillingness to follow such advice due to the perceived high social distance. Finally, the presence of errors and hallucinations in the responses, which are not infrequent, can further discourage the user from adopting the information.

In view of the considerations made and the results obtained from the literature review conducted so far, it would be premature to define ChatGPT as a flawless and perfect tool. However, it clearly represents a very promising technology which, if further developed and refined, has the potential to replace all the other sources of information sources studied in this research. However, as things stand today, confidence in it is still fragile due to the limitations outlined above.

Therefore, while recognizing the future potential of GenAI and ChatGPT, the current state of research supports the conclusions that e-WOM and online reviews remain more effective in generating purchase intention. Hypothesis H1 of this research can therefore be formulated as follows:

*H1: Online reviews have a stronger positive influence on the intention to purchase technological devices than ChatGPT recommendations.*

### 2.1.2. The Mediating Effect of Perceived Risk Between Information Source and Purchase Intention

This section will examine in greater depth the indirect effect carried out by perceived risk on the relationship between online reviews, ChatGPT-based recommendations and purchase intention. The aim is to identify which type of online content triggers a greater decrease in perceived risk, thereby leading to a more positive effect on purchase intention. The scientific evidence regarding the two distinct parts of the mediation effect will then be formalized in hypotheses H2 and H3, which will reflect the key insights emerging the current literature on this topic.

It is important to note that many papers used to investigate H2 identify purchase intention as the dependent variable in their models. Therefore, these studies were also taken into consideration to examine the second effect of mediation (i.e., the relationship between perceived risk and purchase intention) and to formulate the related research hypothesis (H3). Furthermore, as already mentioned, this relationship is widely documented in the current literature. However, in addition to the studies mentioned above, more research was cited that specifically focuses on the relationship between the mediator and the dependent variable, providing additional support for that specific part of the proposed mediation model.

The distant and impersonal nature associated with using a global, open-to-everyone platform like the Internet makes the perception of risk a vital component of online shopping for today's consumers (Pavlou, 2003; Lee

& Turban, 2001). As a matter of fact, this feeling is significantly higher in online shopping than in physical shopping, which is why it is crucial for consumers to implement strategies to decrease the degree of uncertainty (Lee & Tan, 2003; Laroche et al., 2005; Lee & Turban, 2001; O'Cass & Fenech, 2003).

Based on the results of many papers analysed so far, searching for product information online is a process that significantly reduces these psychological discomforts. When there is no opportunity to judge product quality and seller truthfulness in person, many consumers rely on online costumer reviews to get a better idea about the products they are interested in, listening to a generally impartial source (Yaylc & Bayram, 2012; Peterson & Merino, 2003; Bai et al., 2015). Through these contents, consumers can share with anyone their experiences with the products they have purchased. In addition to all the other reasons they are useful in improving consumers' consumer journey, as has already been said, they serve to decrease the level of perceived risk associated with the purchasing decision-making process (Hussain et al., 2017; Park et al., 2007; Akroush & Al-Debei, 2015; Han & Windsor, 2011; Lam et al., 2023). Indeed, before finalizing a purchase, many individuals seek out opinions from other customers who have previously purchased the product and provided a review accessible to all Internet users (Almana & Mirza, 2013; Gibreel et al., 2018). Compared with the traditional WOM, which is restricted to well-defined geographic boundaries, the e-WOM manifests itself with a considerably larger number of participants, active and passive, and with a significantly greater quantity and quality of information cues (text, pictures and videos), thus presenting the ability to reduce the level of risk associated with purchasing more than the previous one (Zhao et al., 2017).

However, despite the undeniable convenience and immediacy of searching for information and purchasing products online, its use raises new issues that can be summarized as the perceived risk of online consumers, including fraud, misuse of personal data, partial inability to evaluate products, and many others (Ventre & Kolbe, 2020).

According to Ko et al., (2004) perceived risk is defined as "*the potential for loss in pursuing a desired outcome from online shopping"* (p.21). Likewise, Dowling and Staelin (1994) defined this concept as *"the consumer's perceptions of the uncertainty and adverse consequences of buying a product or service"* (p.119). In other words, it is the possibility, manifested within the consumer's mind, that something could go wrong in the context of purchasing a product (Featherman & Pavlou, 2003).

With regard to hypothesis H3, which concerns the second part of the mediation effect, there are now countless studies that have confirmed the inverse relationship between the mediating variable (perceived risk) and the dependent variable (purchase intention) of the proposed model (Miyazaki & Fernandez, 2001; Pelaez et al., 2017; Bhatnagar et al., 2000; Farivar et al., 2017; Chiu et al., 2014; Singh & Srivastava, 2018; Hong & Cha, 2013; Liu & Wei, 2003; Kim & Lennon, 2013; Akhlaq & Ahmed, 2015; Han & Kim, 2017; Pavlou, 2003; Kim et al., 2008; Van der Heijden et al., 2003; Soleimani et al., 2017; Park & Tussyadiah, 2017). This body of research has consistently demonstrated that lower levels of perceived risk are associated with a greater intention to purchase and vice versa. However, even during the examination of the less intuitive part of the mediation effect (hypothesis H2), which explores the relationship between the independent variable (information source) and the mediating variable (perceived risk), numerous papers that also employ purchase intention as the dependent variable will be cited. These studies offer further empirical support and reinforce the validity and the rationale behind H3.

At this stage, it is necessary to conceptualize the variable perceived risk, providing its definition and outlining the structural dimensions that it has been given over time by the existing literature. Then, the primary focus of this paragraph will concern the analysis of the studies that have incorporated perceived risk as a mediator variable within the relationship between online reviews/ChatGPT recommendations and purchase intention. In doing so, this section builds on the scientific insights reported and discussed in the previous paragraph, expanding on them with key findings that highlight the potential modifying role of perceived risk within this correlation.

Mitchell (1999) spoke of perceived risk as a *"multidimensional phenomenon"* which can manifest itself in a variety of ways and circumstances, and for this reason must be segmented into different components. A well-known framework that has been used for analysing the concept of perceived risk is that conceptualised by Ariffin et al., (2018), which divides it into six dimensions: *financial risk*, *product risk, security risk, time risk*, *social risk and psychological risk.* In turn, this model was created from previous research that demonstrated the validity and importance of the single components (Dai et al., 2014; Masoud, 2013; Jacoby & Kaplan, 1972). Below are the definitions of each:

- *Financial risk*: the probability borne by the consumer of suffering a loss of money or that the good purchased is not worth the price paid (Featherman & Pavlou, 2003).
- *Product risk*: the likelihood that the product purchased online will not meet expectations in terms of quality and features (Zheng et al., 2012).
- *Security risk*: the possibility of the online user being a victim of fraud, hacking, and any improper disclosure of their personal or financial data (Soltanpanah et al., 2012).
- *Time risk*: includes the expected time to perform all actions related to the online purchase, from browsing of product information, making the purchase to waiting for products to be delivered to your home (Dai et al., 2014; Ko et al., 2004).
- *Social risk*: the consumer's perceived possibility that the product will cause dissatisfaction among friends and family (Dowling & Staelin, 1994).
- *Psychological risk*: the possible post-purchase frustration arising from the knowledge that one has chosen the wrong product (Ueltschy et al., 2004).

According Ariffin et al., (2018), only social risk was found to be not significant in influencing purchase intention in the context of clothing, while security risk was the most influential dimension (Ariffin et al., 2018). Based on much research that has investigated in depth the impact of perceived risk on the dependent variable, it appears that the first three dimensions mentioned (financial, product and security risk) are the most crucial in shaping consumers' purchase intention (Bhatnagar et al., 2000; Chen & Barnes, 2007; Kim et al., 2008; Dai et al., 2014; Ariff et al., 2014; Senecal 2000; Borchers 2001; Zheng et al., 2012; Featherman & Pavlou, 2003; Forsythe & Shi, 2003; Masoud, 2013; Paluch & Wunderlich, 2016; Bhatnagar et al., 2000).

Indeed, among the various risk categories, concern for one's sensitive data and privacy emerges as a key issue for most consumers. It is not uncommon for consumers to refrain from using certain web sites or making online purchases to keep their data safe (Tsai & Yeh, 2010). This situation is extensively documented in today's literature, considering also the previously mentioned studies. Conversely, social risk consistently emerges in many of the studies reviewed as a less critical component, compared to the other dimensions of perceived risk. However, according to the study by Shang et al., (2017), fear of judgment from others (family members, friends, etc.) inhibits purchase intention, both behaviourally and neurologically, showing that this factor is crucial in influencing the dependent variable and deviating to some extent from the rest of the literature.

According to Hong & Cha, (2013), the perception of product risk, financial risk, psychological risk and security risk, exert a direct and negative effect on purchase intention. In the context of online apparel shopping, Almousa (2011) identified product risk, time risk and privacy risk appear to be the most important dimensions in reducing consumers' purchase intention. Similarly, in the sector of private labels in India, Bhukya & Singh (2015) analysed three dimensions of risk (product, financial and psychological), all of which were all found to be significant in decreasing consumer purchase intention (Bhukya & Singh, 2015).

The perception of risk and the importance attributed to individual dimensions varies significantly based on the demographic and cultural characteristics of consumers. Park & Jong-Kun (2003) have proven that Korean consumers are more risk-tolerant than American consumers (they showed higher levels of purchase intention with the same level of perceived risk). Most probably this happens because of the so-called *"cushion effect"*, which can be defined as the social protection perceived by individuals living in collectivist cultures (such as Korea) that would explain the greater propensity for risk. Furthermore, Ko et al., (2004), have demonstrated that American consumers are more sensitive to financial and time risk, whereas Koreans are more sensitive to psychological and social risk. Instead, Liebermann & Stashevsky (2002) found that Israeli consumers focus more on privacy and financial risk, while American consumers prioritize time risk.

The analysis of these initial papers was intended to identify the dimensions of perceived risk that most impact the purchase intention, with particular emphasis on highlighting the negative correlation between the mediating variable and the dependent variable of the model. This preliminary study will be crucial when hypothesis H3 will be formulated. In contrast, the examination of the first part of the indirect effect (namely, the relationship between the independent variable, distinguished in its two variants, and the mediator), represents a more challenging research question to examine, as it is less straightforward and less addressed in the literature as the previous one.

Consumers are seeking to minimize the level of perceived risk when shopping online, and both reviews found on the Internet and advice offered by Artificial Intelligence, particularly ChatGPT and the new *Large Language Models*, have been shown to help the user in this regard. As in the preceding paragraph, the review will begin with papers that focus on the influence of perception of risk on the relationship between e-WOM and purchase intention, followed by the analysis related to AI-based recommendations. This breakdown will necessarily be much briefer, due to the greater specificity of the relationship to be studied and the significantly smaller number of papers that investigated this topic compared to the previous one.

Zhao et al., (2017), in their study on the Chinese online agricultural products market, demonstrated that the breadth and media richness of online customer reviews have a positive impact on the reader's purchase intention by reducing their perceived level of risk. Within the same context, a Korean study measured the impact of online reviews on the consumers' intention to visit a restaurant for the first time (T1) and for a subsequent time (T2), considering the impact of performance risk (a concept similar to product risk) and financial risk. The reviews proved to be especially useful in stimulating a first visit through a significant reduction in performance risk. Conversely, financial risk had a more pronounced effect in encouraging a second visit. This suggests that in the first stages consumers are more concerned about the service quality, instead the repeat consumers are more concerned about a potential monetary loss. These findings highlight the evolving nature of the perceived risk across the consumer journey (Huifeng & Ha, 2021). This research extended an earlier paper by Huifeng et al., (2020), which had found that only financial risk negatively impacts visit intention.

Gender differences also emerge as a key variable in influencing perceived risk levels and consequently purchase intention. As already seen in the previous paragraph, Bae & Lee (2010) have shown that women perceive more risk in online shopping than men, and that e-WOM is particularly useful for reducing this elevated level of uncertainty. This happens because women attribute greater importance to the judgment of others to reduce uncertainty and validate their choices, which coincides with the so-called *social risk*, analysed previously. More specifically, it seems that women's purchasing intention is more susceptible than men's to both positive and negative reviews, with negative reviews having a greater impact on both genders than positive ones, the *"negativity effect"*. A study examining the role of e-WOM in generating purchase intention among female travellers in India has shown that this effect exists only when there is a reduction in perceived risk. This discovery supports earlier research by highlighting the importance of the mediating effect of this variable is shaping behavioural outcomes, especially for women (Islam et al., 2024).

A third body of research investigates the perceived credibility and informational value of e-WOM content, and how these attributes interact with the feeling of risk. As mentioned in the last paragraph, Hussain et al.,

(2017) proved the significance of the credibility of the e-WOM source (divided into the 4 dimensions: experience, reliability, objectivity, homophily) in promoting information adoption by lowering the level of perceived risk. In support of these results, two studies conducted in Indonesia have shown that the perceived informational value derived from online customer reviews enhances purchase intention by lowering perceived risk (Helfiyana et al., 2024; Sembiring & Nisa, 2024). By contrast, the work of Bathar & Muda (2016), despite sharing some similarities with the previous ones, represents a stand-alone case. As a matter of fact, they found that User-Generated Content (UGC) on Instagram has a substantial impact on increasing user purchase intention through a mediated effect of perceived credibility and usefulness. However, in this case the perceived risk seems to have a negative effect, the opposite of that found in other studies, indicating the complexity of the relationship between perceived risk and e-WOM in certain digital contexts.

Other scholars have shown how the structure and clarity of reviews are key factors in influencing risk perception. For example, in the context of online marketplaces, the absence of feedback (missing reviews following a transaction) seems to raise the perception of risk associated with the purchase, which in turn causes a lowering of purchase intention (Hwang & Han, 2023). In the same way, confusion resulting from online reviews, divided into *ambiguity confusion* (vague or unclear reviews) and *similarity confusion* (reviews that are too similar to each other), is significantly correlated with an increase in online shopping cart abandonment via an increase in perceived risk (Roy & Shaikh, 2024). On the other hand, contrary to what Roy & Shaikh (2024) demonstrated about the effect of ambiguity in online reviews, Yang et al., (2016) came to the conclusion that the balance between positive and negative reviews regarding a product seems to significantly increase the intention to purchase among online buyers through a reduction in perceived risk (composed of performance risk, the most influential, financial risk, psychological risk and social risk).

This conceptual model has also been extensively validated using theoretical frameworks already seen in previous sections of this research. A study in Vietnam demonstrated via the *Information Acceptance Model* (IACM) that the four dimensions of perceived usefulness of e-WOM (quality, credibility, need for information and attitude towards information) significantly increase purchase intention in e-commerce platforms (Shopee and Lazada) through a decrease in perceived risk (Cuong et al., 2024). Instead, Using the *Stimulus-Organism-Response* model, Yadav et al., (2024), analysed the impact of online costumer reviews (S) in increasing travel behavioural intentions (R) through lowering perceived risk (O). As expected, all hypotheses of the mediation model were confirmed, providing further evidence of the usefulness of e-WOM in lowering online consumers' feelings of risk.

One last confirmation comes from the paper by Gavilan et al., (2019), which investigates how online numerical evaluations influence the movie selection process. It emerged that in this context rating significantly helps decision making and intention to enjoy content through a decrease in perceived risk, divided into global, temporal, financial, and experiential. Additionally, the study highlights the moderating role of an individual’s *susceptibility to interpersonal influence* (SRI). Participants more prone to social influence perceived even greater value from ratings in terms of both ease of decision-making and risk reduction, especially for global and temporal risk.

Overall, the literature clearly shows that perceived risk plays a crucial mediating role in the relationship between e-WOM and purchase intention. In most studies, e-WOM reduces various dimensions of perceived risk, such as performance, financial, social and psychological risk, which in turn increase consumers' willingness to buy, although some articles highlight exceptions or context-specific nuances.

Moving on to the influence of perceived risk on the relationship between generative AI, in particular ChatGPT, and purchase intention, this variable has emerged as a critical issue in the current literature on this topic, even though it is a very recent technology and therefore an equally recent line of research.

One of the most consistent and recurrent concerns regarding the use of this technology to obtain information about products and services is represented by the fear of privacy and data security violations. Arce-Urriza et al. (2025) highlight that, despite the greater usefulness of chatbots following the advent of Generative AI, these risks negatively influence users' willingness to adopt ChatGPT for product-related information. Similarly, Silalahi (2024) confirms that privacy risk significantly weakens the effect of trust on information adoption, particularly in the context of sustainability recommendations. The same conclusions are drawn by Zhou & Wu, (2024) and Hu et al., (2024). Finally, earlier research highlights that women are significantly more concerned than men about online data privacy and security (Sheehan, 1999).

The study conducted by Abou-Shouk et al., (2024), already referenced in the previous paragraph, represents further confirmation of how concerns about privacy and personal data constitute a crucial deterrent to the intention of using tools like ChatGPT. Indeed, elements such as the usefulness, credibility and perceived intelligence of this technology are not enough to cancel out the negative effect of these factors. This cross-cultural investigation, conducted between Oman and the UAE, showed that Omani users are more sensitive to these issues than Arab ones, thereby highlighting the impact of the different degrees of digital maturity and trust in technological systems across industrialized and non-industrialized countries. Although not specifically emphasized in the paper, such fears coincide with the conceptualization of perceived security risk proposed by Ariffin et al., (2018), whose validity in mediating the relationship between ChatGPT recommendations and purchase intention has been widely proved.

In addition to issues related to data security and privacy, ethical issues (Alamri, 2025) and the perceived risk of receiving incorrect information (Kim et al., 2023c) also appear to significantly hinder the use of GenAI for purchasing purposes.

Another set of studies focuses on a specific technology-related psychological discomfort, called *technology anxiety*. This is defined as the feeling of apprehension and nervousness that is perceived when interacting with a technology whose reasoning and functioning is unknown. According to research by Seyfi et al., (2025), this factor significantly reduces the intention to use ChatGPT to receive travel recommendations. Likewise, a study conducted on UAE university students, found that the attitude and intention to use ChatGPT for educational purposes significantly decreases in the presence of high perceived risk and technology anxiety (Sallam et al., 2024). In addition, according to Murshidi et al., (2024), a complete knowledge regarding ChatGPT, including its benefits and risks, can lead to greater user's caution and a lower probability of adopting the tool.

Beyond psychological and security-related concerns, a broader analysis of risk dimensions was carried out by Han et al. (2024), who employed the model proposed by Ariffin et al. (2018) and confirmed the negative impact of five out of six dimensions of perceived risk, i.e., all except social risk, on the intention to adopt the information provided by ChatGPT in the tourism sector. Similarly, the study conducted by Sefa & Yilmazel (2025) found that the use of GenAI significantly increased levels of time, privacy, social, psychological, and security risk, discouraging the use of these tools. On the other hand, product and financial risk were not found to significantly influence the dependent variable. This result testifies to how users generally trust the rationality and technical reliability of GenAI, yet usage is heavily deterred due to broader socio-ethical implications.

Another dimension of perceived risk that psychologically hinders the use of ChatGPT to obtain product recommendations is so-called transparency anxiety, conceptualized and explored in depth in the paper by Huang et al. (2025). It represents the fear stemming from an inability to understand how this technology generates its recommendations, which are often perceived as opaque, inexplicable or arbitrary. The authors have shown that this feeling negatively mediates the relationship between the anthropomorphism of the chatbot and the acceptance of recommendations, proving to be another important deterrent to the usage of these algorithms.

Although most of the studies analysed showed that ChatGPT triggers various components of perceived risk, one exception is represented by the research conducted by Ramrath et al. (2024). The authors showed that ChatGPT's perceived proficiency in solving objective tasks, such as mathematical problems, actually has the ability to increase the intention to use this tool by decreasing the feeling of risk. Although such findings are more limited, they suggest that under specific conditions, specifically when the task is perceived as logical or numerical, ChatGPT may help mitigate perceived risk rather than amplify it.

In conclusion, the literature clearly shows the significance of perceived risk as a mediating factor within the relationship between the recommendations of generative AI, more specifically from tools such as ChatGPT, and users' intention to purchase or adopt information. However, unlike to the previous case, this mediation turned out to be almost always negative and inversely proportional: in most of the studies analysed, concerns about privacy, data security, ethical doubts, misinformation, technological and transparency anxiety emerge as strong inhibiting factors. These factors weaken trust and greatly constrain information adoption, especially in more sensitive contexts and characterized by lower levels of technological education.

Overall, perceived risk tends to have a robust negative mediating effect, dampening the persuasive power of GenAI-generated recommendations across various areas and user groups. Without going into too excessive detail, it is clear from the current research on the subject that e-WOM and online reviews generally lead to a decrease in perceived risk, while Generative AI technologies and ChatGPT produce the opposite effect, increasing perceived risk, which becomes a significant barrier to adoption. As previously highlighted, despite the innovativeness, undoubted capabilities and immense potential of ChatGPT, trust in this tool is still precarious compared to more established peer-based sources of information like e-WOM.

Based on the formulation of hypothesis H1, and the additional discoveries coming from this second literature review, hypothesis H2 and H3 can be articulated as follows:

*H2: Perceived risk mediates the relationship between the source of information (online reviews vs. ChatGPT recommendations) and purchase intention, with online reviews decreasing perceived risk more than ChatGPT recommendations.*

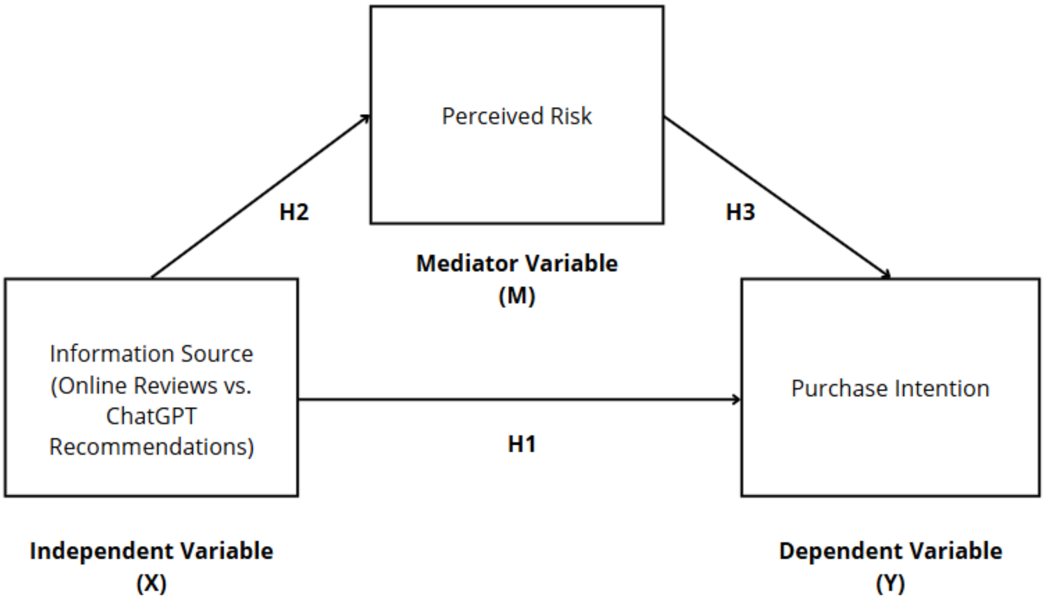
*H3: Perceived risk mediates the relationship between the source of information (online reviews vs. ChatGPT recommendations) and purchase intention, with lower levels of perceived risk leading to a higher intention to purchase technological devices.*

### 2.2. Conceptual Framework

The primary objective of this experimental study is to investigate how distinct types of information sources used to obtain product advice (specifically, online reviews vs. ChatGPT recommendations) influence consumers' purchase intention of electronic devices in the technology sector. To test this relationship, it was decided to fill the conceptual framework through the indirect effect represented by the mediating factor perceived risk generated by the information source. Accordingly, the developed research model includes perceived risk as a mediator, information source as a dependent variable and purchase intention as a dependent variable.

For the development of the conceptual framework, Model 4 from Andrew F. Hayes' (2017) PROCESS macro was adopted, which is characterized by the presence of an independent variable (X), a dependent variable (Y), and a mediator (M).

Considering the results discussed in the last two paragraphs and the formulation of the corresponding research hypotheses, the conceptual model of the research can be illustrated as follows:




Mediation model (How/Mediation design): the independent variable (X) consisting of the manipulation of the information source (online review vs. ChatGPT recommendation) influences the dependent variable (Y) identified in the purchase intention through the mediation of the mediating variable of the degree of perceived risk (M).

# Chapter 3 - Experimental research

## 3.1. Methodological approach

### 3.1.1. Methodology and study

The present experimental study consists of a conclusive causal Between-subjects 2x1 research design. The results of the experiment are represented by responses to a questionnaire obtained through a self-administered survey conducted in Italy during April and May 2025 using the online platform Qualtrics XM. Specifically, survey participants were selected by adopting a non-probabilistic sampling methodology. It was decided to use a convenience method thereby taking advantage of the ease and speed of accessing and selecting elements of the target population. As a matter of fact, this technique implies no economic costs and results to be advantageous in terms of high speed of data collection and high response rate. Considering the target sample, it was chosen to include respondents from all age groups and belonging to all genders, as it was not expected that demographic variables could affect the results of the experiment in a statistically significant way.

### 3.1.2. Participants and sampling procedure

The survey was distributed to 198 individuals of whom 191 respondents fully participated in the experimental study by answering all the questions within the questionnaire structure. The remaining 7 incomplete responses were first selected and later discarded from the dataset during the data cleaning procedure. Specifically, respondents were contacted through an anonymous link generated by the Qualtrics XM online platform and subsequently sent through instantaneous messaging applications and social media networks as main distribution channels (WhatsApp, Instagram). The sample of the target population reached by the survey included mainly university students and newly hired workers but also a non-negligible number of adults located in different cities in Italy. Therefore, following this assumption, the average age of the respondents was found to be 34.42 years, although the age range fluctuated between a minimum of 18 and a maximum of 67 years. As can be seen, the average age is higher than the most representative age group in the sample (22-26 years, which includes 49.2% of participants, with 94/191 responses) due to the presence of a modest amount of people over the age of 50, which significantly increases the average. Regarding the gender of the respondents, the prevailing gender was female, represented by 54.5% (104/191), while males accounted for 41.9% (80/191). The remaining 3.7% (7/191) of respondents selected the third gender/non-binary option (2.1%; 4/191) or preferred not to identify with a specific gender (1.6%; 3/191).

### 3.1.3. Data collection and questionnaire composition

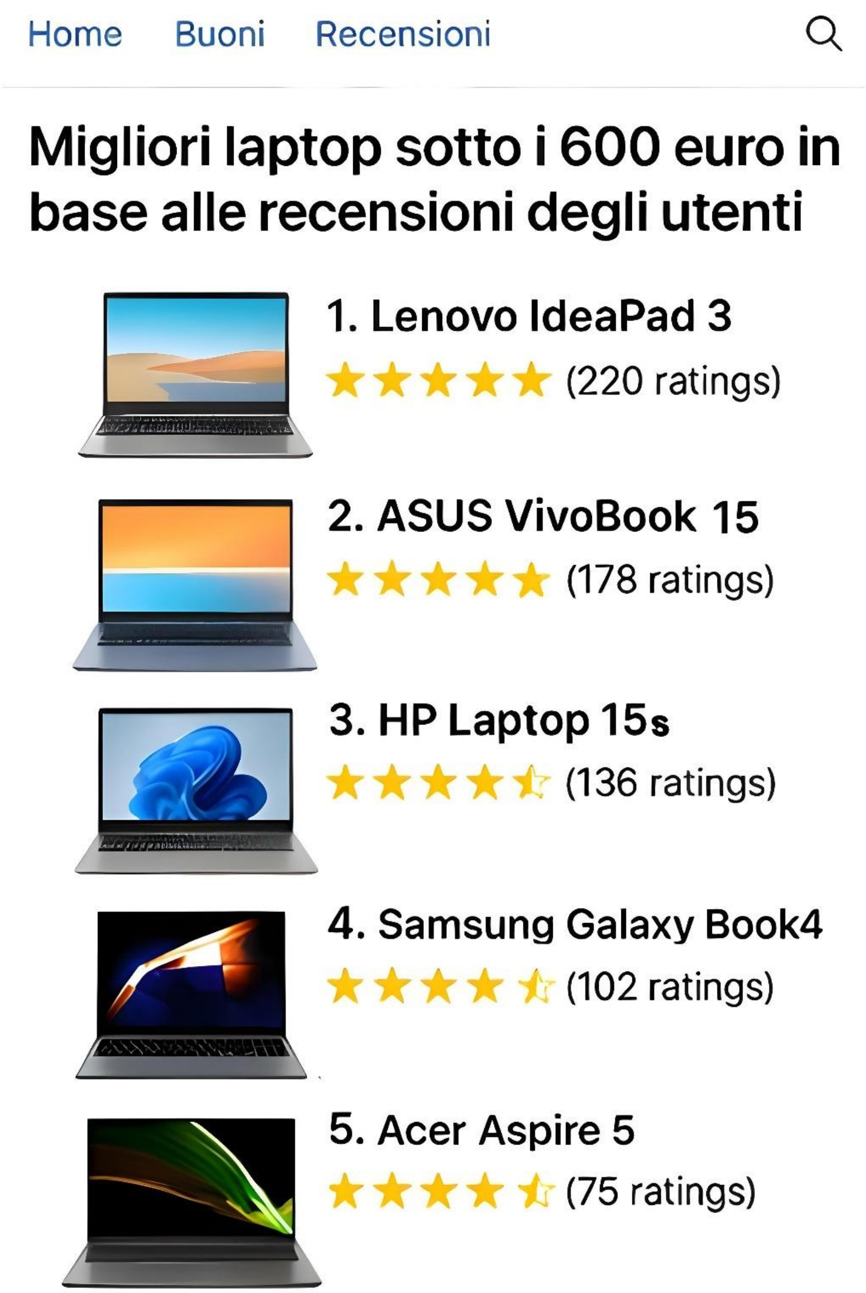
To conduct the experimental study, a questionnaire consisting of eight questions was developed, six of which were specific and two were demographic.

To manipulate the independent variable (Information Source: Online reviews vs. ChatGPT Recommendations), it was essential to create two visual stimuli, each different from the other. The first scenario is represented by an image depicting the user interface of an unidentified e-commerce website showing a ranking of laptops based on numerical reviews (from 1 to 5 stars) submitted by hypothetical online users who have previously purchased those products.

Regarding this picture, although it does not technically show an example of e-WOM, it is important to clarify the rationale behind its layout to avoid potential misinterpretations. An alternative depicting individual user reviews and comments (which, by definition, represent e-WOM) would likely have generated higher levels of risk and lower purchase intentions. This is because these images would have failed to capture the intrinsic and aggregated nature of a tool such as e-WOM, which includes the total amount of available opinions posted on the Internet about a given product.

In contrast, the image used to represent ChatGPT, which is displayed later, represents a ranking, which implies a preliminary analysis of a series of data, thereby being typically perceived as more useful than isolated reviews. To ensure the perception of equal usefulness and analytical robustness of the two visual stimuli, it was decided to show, for the e-WOM condition, an interface that theoretically represents an output of an algorithm. However, this ranking is entirely based on fictional user reviews, being conceptually consistent with the definition of e-WOM.

For this reason, and in order to provide both visual stimuli with a perception of “equal usefulness,” it was decided to show an interface that represents under a theoretical level a ranking made by an algorithm, but that in reality is based only and exclusively on simulated user reviews, and thus be considered a tool that represents e-WOM and cumulates its individual manifestations. This clarification was necessary to prevent any misinterpretation of the image as something that conceptually deviates from e-WOM and the opinions of human users.




The second scenario consists of an image showing a simulation of a response provided by ChatGPT that presents the same ranking shown in the previous image, replicating its structure. Specifically, the stimulus simulates a typical AI-generated response in relation to a specific question, namely a hypothetical consumer asking for a ranking of the five best laptops available within a predetermined budget.


In this regard, additional clarification is needed regarding the visual stimuli presented to properly contextualize their meaning and to better understand the research objectives. Both scenarios were specifically designed to minimize the likelihood of the manifestation of cognitive biases and any brand-related sentiment conditioning during the participants' completion of the survey. To achieve, visual conditions were artificially and arbitrarily created through the Canva application.

The first scenario represents a mock-up of a user interface from an undefined and fictitious e-commerce website. More in detail, it shows a section of this hypothetical platform dedicated to displaying users' numerical reviews regarding the products in question. The interface portrays no references to existing applications or recognizable design elements, to avoid cognitive constraints related to brand recognition. Equally, in the second prompt, although the content clearly resembles a typical answer of an artificial intelligence (evident from certain features, such as the presence of a logo, the beginning of the response that echoes part of the user's hypothetical question, the use of emoticons, and the accuracy of the answer), there is no specific mention that it is ChatGPT. Again, it was decided to minimise brand-specific bias while preserving the recognisability of AI-generated content. Furthermore, it is essential to emphasize that the ranking of computer brands is completely the same regardless of the scenario displayed. This graphical choice was made with the sole intention of isolating and testing the possible preference for one source of information over another (i.e., online review vs. ChatGPT) regardless of the content provided by each. The purpose was to ensure that the choice depended as much as possible on the stimulus displayed rather than on the analytical consistency of the ranking. Finally, in order to further reduce the impact that the actual content of the two rankings could have on the mediator and the dependent variable, and in order to conceptually highlight the sources of information displayed (i.e., online review vs. ChatGPT), the content of the rankings is plausible, but many different sources of information, both human and artificial, were used as references for their composition.

Returning to the data collection methodology, as mentioned above, responses were collected using a questionnaire, whose structure can be divided into four main parts.

At the beginning of the questionnaire, participants are shown a brief introduction that contextualizes the topic and explains the academic purpose of the experimental research they will be participating in. In addition, after mentioning the university's credentials, respondents were guaranteed full compliance with privacy regulations regarding anonymity in data collection and processing.

The second part of the survey consists of a randomized block comprising two distinct scenarios, which have been described and commented on above. Specifically, the inclusion of the randomization process was fundamental to the structure of the questionnaire to obtain a uniform number of exposures to both visual stimuli.

The third part of the survey is shown to respondents after they have been exposed to one of the two scenarios. Specifically, this section of the questionnaire comprises six questions: the first three concern the mediator (perceived risk) and the other three relate to the dependent variable (purchase intention). All questions were evaluated using a seven-point Likert scale.

The first scale, used to measure the mediating variable, comes from the scale validated by Cox, A. D., Cox, D., & Zimet, G. (2005). Understanding consumer responses to product risk information. *Journal of Marketing*, *70*(1), 79–91.

The second scale, relating to the dependent variable, derives from the scale validated by Dodds, W. B., Monroe, K. B., & Grewal, D. (1991). Effects of price, brand, and store information on buyers’ product evaluations. *Journal of Marketing Research*, *28*(3), 307-319.

Both scales were adapted to the needs of the experimental research. For this reason, the three items considered most useful and relevant to the purposes of the experiment were selected and shown to the participants.

Finally, the fourth and last part of the questionnaire consists of demographic questions, in which the gender and age of the respondents were requested.

### 3.2. Experimental results

#### 3.2.1. Data analysis

The data collected through the questionnaire created using the Qualtrics XM platform was exported to SPSS (Statistical Package for Social Science), a statistical software program for analysis.

Initially, it was decided to perform two exploratory factor analyses to examine and validate the items of all scales used in the conceptual model structure of the experimental research. Specifically, a principal component analysis was performed as the extraction method, applying Varimax as the rotation technique. To decide how many factors to extract, the table of total variance explained was observed, verifying that, according to Kaiser's rule, the eigenvalues were greater than 1 and the cumulative variance in percentage was greater than 60%. In addition, both the table of commonalities and the component matrix were observed. Specifically, all items showed an extraction value greater than 0.5 and a loading score greater than 0.3. Therefore, considering the results obtained, it was decided to keep all the items that make up the scales, thereby validating them.

After validating both scales, two reliability tests were conducted to verify the level of reliability of the scales considered. Specifically, the Cronbach Alpha value of both constructs was observed, ensuring that it was above 60%. Regarding the first scale of the mediator (perceived risk), a value of 0.928 was found, while for the second scale belonging to the dependent variable (purchase intention), a value of 0.955 was recorded. Therefore, in view the results obtained, both scales were considered reliable.

Finally, the KMO (Kaiser-Meyer-Olkin) test was performed to measure the adequacy of the sampling. For the first mediator scale (perceived risk), a value of 0.748 was reported, while for the second scale of the dependent variable (purchase intention), a value of 0.766 was registered. Therefore, in both cases, the level of adequacy was more than adequate (> 0.6). Subsequently, Bartlett's sphericity test was performed, which was statistically significant, finding a p-value less than 0.001 in both cases ($p\text{-value} < \alpha = 0.05$).

#### 3.2.2. Hypotheses results

After performing both factor analyses and reliability tests, the main assumptions of the conceptual model were examined to confirm or reject its statistical significance and, therefore, its relative success.

**H1**

To verify the statistical significance of the direct hypothesis (H1), a comparison of means was performed using a One-Way ANOVA to verify the effect of the independent variable (source of information: online reviews vs. ChatGPT recommendations) on the dependent variable (purchase intention). Specifically, the independent variable (X) is nominal categorical and is divided into two different conditions coded as 0 (ChatGPT recommendations) and 1 (online reviews), while the dependent variable (Y) is continuous metric.

After conducting the ANOVA, observing the descriptive statistics table, it was possible to note that the group of respondents subjected to the scenario coded with 0 (96 people) recorded an average Y of 3.4444, while participants exposed to the visual condition labelled with 1 (95 people) recorded an average Y value equal to 5.2246. Furthermore, considering the ANOVA table, a p-value for the F-test less than 0.001 emerged, which is statistically significant (p-value $< \alpha = 0.05$). Therefore, a statistically significant difference was found between the group means, thus confirming the effect of X on Y. The direct hypothesis H1 (main effect) was therefore proven.

**H2-H3**

To test the statistical significance of the indirect hypothesis (H2-H3), a regression analysis was conducted using Model 4 of the SPSS Process Macro extension (version 4.0) developed by Andrew F. Hayes, in order to verify the mediating effect caused by perceived risk on the relationship between the independent variable (source of information: online reviews vs. ChatGPT recommendations) and the dependent variable (purchase intention). Specifically, the independent variable (X) is nominal categorical and is separated into two different conditions coded as 0 (ChatGPT recommendations) and 1 (online reviews), while both the mediator (M) and the dependent variable (Y) are continuous metric. To demonstrate the success of the mediation effect, it was necessary to divide it into two individual components: a first effect between the independent variable and the mediator (H2) and a second effect between the mediator and the dependent variable (H3).

**H2**

About the first part of the indirect effect, observation of the SPSS results shows a p-value of 0.0000, a favourable confidence interval (LLCI = -2.2939; ULCI = -1.3355) and a negative regression coefficient β of -1.8147. Therefore, this section of the indirect effect was statistically significant, thus confirming hypothesis H2.

**H3**

As regards the second section of the indirect effect, observation of the SPSS output shows a p-value of 0.0000, a favourable confidence interval (LLCI = -0.7739; ULCI = -0.5378) and, again, a negative regression coefficient β of -0.6559. Therefore, this section of the indirect effect was also statistically significant, demonstrating the inversely proportional correlation between MED and Y and thus confirming hypothesis H3.

In light of the results obtained, since both sections of the indirect effect were statistically significant, it is possible to declare the overall success of the mediation effect, i.e., the indirect effect between the independent and dependent variables. Furthermore, observing the statistical significance of the direct effect analysed in the regression analysis, it was possible to establish that this is a partial mediation.

# Chapter 4 - Discussion and Conclusions

## 4.1. Theoretical contributions

The findings of this study provide a significant and original theoretical contribution to the body of research related to consumer behaviour and the effectiveness of different recommendation sources during the today's consumer decision-making process. In addition to validating the underlying theoretical model, the empirical support of the three tested hypotheses helped to address a notable research gap. This was represented by the lack of a direct comparison between electronic word-of-mouth (e-WOM) and recommendations created by generative artificial intelligence systems, more specifically ChatGPT, particularly in a utilitarian purchasing context such as electronics. The decision to put into contrast these two information sources in the context of this specific and relatively underexplored sector of the consumer economy has allowed the investigation of new research avenues and has challenged some of the assumptions arose in existing literature.

The two sources under examination, e-WOM and ChatGPT, were previously selected due to their representativeness and effectiveness within their respective categories: human-based and AI-generated recommendations. Next, they have been analysed in greater depth through the experimental study just conducted. This comparison aligns with a more comprehensive reflection, discussed from the introductory chapter onward, on the global debate concerning the difference in effectiveness between human and artificial information sources in providing product recommendations. Given the increasing number of people asking product-related information to Generative AI-based chatbots, comparing the efficacy of e-WOM and ChatGPT in reducing perceived consumer risk and enhancing purchase intention represents a particularly innovative and challenging contribution. This examination enables a direct assessment of the influence of a well-established human source against an emerging technology that is increasingly relied for consumption choices.

A careful re-reading of the second chapter, which reviewed the literature related to the key relationships of the suggested conceptual model, reveals that this study has both confirmed and challenged prior findings on the topic. One of the most important theoretical contributions consists in having demonstrated that, despite the growing diffusion of generative artificial intelligence, advice originating from human sources, specifically electronic word of mouth, remains more effective in stimulating purchase intention than recommendations provided by ChatGPT. This discovery is particularly noteworthy considering the current global context marked by growing enthusiasm for AI adoption in decision-making processes, where the persuasive power of technological efficiency and output accuracy is often overlooked (De Bruyn et al., 2020; Haenlein & Kaplan, 2019; Kozinets & Gretzel, 2020; Alexander et al., 2018; Davenport et al., 2019).

Thanks to its ability to handle huge volumes of data, reply in natural language and offer quick, accurate and personalized recommendations, generative AI has been widely promoted as a revolutionary tool in this context over the past few years (Statista, 2023; Capgemini, 2023; Lebow, 2023; Wong et al., 2023; Ali et al., 2023; Abou-Shouk et al., 2024). However, the results of this experimental research highlight a factor that is sometimes disregarded in the quest for innovation: the importance, centrality and resilience of the human component in fostering trust and inspiring purchase decisions. Indeed, human sources of information maintain a long-lasting competitive edge, because they are capable of evoking trust and eliciting authenticity, qualities that even the most advanced AI systems still find difficult to replicate (Bickart & Schindler, 2001; Sulthana & Vasantha, 2019; Court et al., 2009; Cheong & Morrison, 2008). This supports the assumption that the effectiveness of informational sources depends not only on the quality of content, but also from the attitude and trust towards the source of the recommendation (Fu et al., 2020; Huang & Chen, 2006; Mauri & Minazzi, 2013; Xu et al., 2024). Theoretically, this finding reinforces the view that the human aspect of recommendations is still hard to replace and will probably always represent a fundamental reference point for consumers. Although AI can work alongside humans throughout this process, it is unlikely to emulate their relational and psychological impact, which constitute a crucial factor in decision-making dynamics.

A second major theoretical contribution from this research consists of the identification and validation of perceived risk as a key mediating factor within the relationship between the type of information source and purchase intention. Even though ChatGPT's outputs are coherent, detailed, and well-presented, they are not able to reassure the consumer and reduce uncertainty to the same extent as e-WOM, which benefits from perceptions of spontaneity, authenticity, and trustworthiness (Wien & Peluso, 2022; Huang & Chen, 2006). Thus, the risk-reducing function performed by e-WOM is a key element of its persuasive effectiveness, prompting new directions for theoretical models that embed perceived risk as a structural mediator in the relationship between information sources and purchasing behaviour.

The final, but equally important, contribution of this experimental study is represented by the demonstration that even within a utilitarian context like electronics, where rationality, precision, and efficiency in displaying information should theoretically prevail, e-WOM still performs better than ChatGPT in leading to a positive behavioural outcome. As observed in the papers discussed in the previous sections, numerous reviewed studies have already demonstrated across various sectors that e-WOM is generally more effective than GenAI-based recommendations in reducing the perception of risk and increasing purchase intention (Chen et al., 2015; Kour et al., 2024; Kirmani & Ferraro, 2017 ; Yang, 2022; Zhu et al., 2012; Fu et al., 2020; Hussain et al., 2017; Park et al., 2007; Akroush & Al-Debei, 2015; Han & Windsor, 2011; Lam et al., 2023; Zhao et al., 2017; Islam et al., 2024).

While this research confirms that dynamic, it also contextualises and applies it to a consumer sector where AI seemed to have a greater persuasive capacity. In fact, a large body of prior research has testified that in high-cognitive and logic-driven scenarios consumers tend to perceive AI characteristics as more suited to handling such tasks (Dietvorst & Bharti, 2020; Osborne & Bailey, 2025; Ramrath et al., 2024; Xie et al., 2022; Xu et al., 2024; Kim & Duhachek, 2020; Kim et al., 2021; Zhu et al., 2023; Osborne & Bailey, 2025;

Ruan & Mezei, 2022). According to this perspective, the findings of these studies indicate that the precision, rationality, speed and logical capabilities possessed by AI should compensate for its lack of empathy, human-likeness or perceived authenticity. By contrast, the experimental results of this study overturn this theoretical prediction, offering an original and innovative contribution by questioning one of the most widespread assumptions in the recent literature regarding consumer behaviour: that artificial intelligence, especially generative models like ChatGPT, is perceived as the most fitting source of advice in rational and logical consumption settings.

These findings carry theoretical relevance for several reasons. In the first place, they enrich the discussion regarding the social acceptance of AI in decision-making processes. The study strengthens the idea that, despite undoubted technical and logical skills in producing its output, artificial intelligence is not yet perceived as sufficiently "human" to completely replace conventional informational channels. This corroborates the existence of psychological phenomena such as the *human black-box effect* (Haenlein & Kaplan, 2019; Chen et al., 2024; Rese et al., 2020; Leung & Chan, 2020; Go & Sundar, 2019; Ali et al., 2023; Wong et al., 2023; Gupta & Mukherjee, 2024; Bonezzi et al., 2022), which is defined as the consumers' tendency to place more trust in human judgement, since it is perceived as more transparent and comprehensible. Second, the study includes perceived risk as a structural mediating variable in assessing the most valuable information sources for obtaining product-related recommendations. Based on this assumption, the preference for online reviews can be ascribed to its tangible ability to reduce uncertainty, rather than attributed solely to familiarity or habit. This questions the conceptualization of the traditional dichotomy between *cognitive trust* (associated with AI) and *affective trust* (associated with e-WOM), showing that even in logic-oriented contexts, psychological and emotional dimensions play a key role in dictating consumer preferences. Lastly, this research challenges a well-established evidence present in the literature regarding AI in utilitarian purchasing contexts. Despite having a strong ability to produce highly coherent and customised responses, ChatGPT doesn't generate the same degree of perceived credibility or psychological reassurance as human advice. Even in situations where efficiency should theoretically provide a competitive advantage, efficiency alone does not suffice to produce persuasion.

### 4.2. Managerial implications

In addition to enriching the theoretical knowledge of consumer behaviour, the empirical findings of this paper offer several practical insights that managers and companies may use to help them formulating effective marketing strategies in today's digital and interconnected consumer landscape. In particular, the comparison between online reviews and ChatGPT as sources of product recommendation, in the context of a functional and utilitarian product category such as technology, provide pragmatic managerial implications. These breakthroughs are especially relevant in an environment characterized by information overload, growing popularity of Generative AI, and consumers' constant demand for trust, reliability, and reassurance during their costumer journey (Scheibehenne et al., 2010; Chernev et al., 2015; Mittal, 2016; Agnihotri et al., 2024; Kim et al., 2023a; Foroughi et al., 2024; Banker & Khetani, 2019; Rhee & Choi, 2020).

The first and probably most significant managerial takeaway emerging from this research is that, despite remarkable technological developments in recent years, online reviews remain more effective than recommendations provided by cutting-edge artificial intelligence tools, such as ChatGPT, in providing reassurance to costumers and increasing their willingness to buy. As mentioned above, even in rational and functional purchasing contexts such as electronics, consumers prefer opinions from people and not from algorithms, as they are perceived as more reliable and authentic. This implies that businesses should consider automated marketing solutions as complementary to “human” communication channels rather than rushing to replace them.

From a strategic standpoint, managers ought to keep investing in the development and reinforcement of word-of-mouth ecosystems centred on the human element of product recommendations. Specifically, promoting and encouraging the publication of reviews and consumer-to-consumer interactions on digital platforms (e.g. e-commerce websites, social networks, forums), companies can increase consumer engagement and positively influence conversion rates. Being perceived as one of the most reliable, authentic and effective forms of advocacy, marketing and brand initiatives should incentivize satisfied customers to share their experiences in detail. In fact, in a reality increasingly dominated by automation and where the race to generate synthetic and massive artificial content is ever fiercer, human voices become an asset. For this reason, companies that successfully keep strong relationships with their consumers, through transparency, interaction, and genuine engagement, will experience a competitive advantage. Therefore, now, managers should prioritize authenticity over automation, especially when building consumer trust is the aim.

A second critical managerial implication regards the function of perceived risk as a crucial mediator in the relationship between information source and purchase decision. The present research demonstrates that e-WOM’s enhanced efficacy can be traced back to its ability to reduce consumer’s degree of uncertainty. This evidence opens new avenues for communication design, particularly for brands operating in industries where product complexity, price, or novelty may hinder purchasing decisions due to an excessively prominent level of perceived risk. Managers should be aware that, even in utilitarian purchasing contexts, effective communication aims to alleviate costumer anxieties and uncertainties in addition to just describing product features and benefits. Reporting previous customers’ experiences, highlighting satisfaction rates, integrating the possibility of giving real-time feedback, or creating active user communities represent feasible strategies that can help remove psychological barriers that slow down or hinder purchases.

Moreover, the tone and the structure, representing key elements of product-related recommendations, directly influence the perception of risk. Watching content generated by real users, especially when it comes to reviews accompanied by images, detailed descriptions, and balanced evaluations, has a positive impact on a consumer's emotions and thoughts. Despite being quick and logical, AI-generated suggestions often struggle to elicit the same level of reassurance and credibility. Therefore, companies should conceive communication strategies aiming to reassure consumers and not just inform them, placing consumer-to-consumer interactions at the heart of brand experiences.

Going on with the implications, the outcomes of this empirical research invite deep reflection from companies that are rapidly integrating generative artificial intelligence into their consumer communication processes. Despite the relative advantages of this breakthrough technology, such as important levels of personalization, speed, and accuracy, its attractiveness is still heavily hampered by widespread scepticism regarding the quality of the outputs offered by artificial information sources. This observation suggests that, at least in the short to medium term, AI should be considered as a valuable operational support tool, rather than a real replacement of creativity and human intuition. In the same vein, companies should adopt strict policies regarding transparency in AI usage, outlining clearly the characteristics and constraints of such systems, and incorporate them into hybrid communication and marketing processes that combine human and artificial content.

An effective application of the insights gained from this experimental research could consist in offering, within the same e-commerce interface, both ChatGPT-generated recommendations and a curated selection of the best human reviews, allowing consumers to choose freely what kind of source to use for product information. Hybrid recommendation systems can thereby maximize the perceived reliability of the information provided, as consumers will choose the source that they personally consider most accurate. Additionally, companies should invest in activities aimed at overcoming barriers to trust in AI, such as explainability of outputs, customer education regarding AI efficacy, and the integration of external endorsements (e.g., expert evaluations, quality certifications). Only in this way can the full potential of AI be exploited without jeopardizing the relation capital that has been established with costumers.

Another significant implication is related to the need to adapt communication tactics to accommodate consumers' varying levels of trust. Even though younger generations are more inclined to rely on AI, because of their greater familiarity with technology, many segments of the population still place greater trust in human recommendations. This indicates that trust in artificial intelligence is not a factor that manifests itself homogeneously, and that companies should segment their consumer base according to this assumption. For this reason, marketing and communication plans should be tailored according to varying degrees of consumers' propensity to trust artificial versus human sources. CRM data and behavioural analytics can help identify which users are more likely to trust human-generated reviews and which are more receptive to AI-mediated suggestions.

The dynamic customisation of e-commerce product pages, automatically showing more human evaluations to users characterized by preference for texts perceived as authentic and real and AI-based suggestions to those more oriented toward efficiency could be an effective application of the empirical results of this research. In this way, firms can create more adaptable, agile, and high-performing recommendation templates.

### 4.3. Limitations and future research

This experimental research yielded interesting theoretical and managerial results, providing a new perspective regarding the comparative effectiveness of human (e-WOM) and artificial intelligence-generated (ChatGPT) sources in stimulating the intention to purchase electronic products. Besides the insights and practical applications, several limitations must be recognised. In addition to reinforcing the interpretative rigor of the study, a critical examination of these elements provides fertile ground for future research aimed at expanding or refining the proposed model.

A first significant limitation is represented by the composition of the sample. As a matter of fact, the convenience sampling method was used for research purposes, which is based mainly on the participation of individuals belonging to the same geographical and cultural context. Although this sampling method significantly facilitated the speed and ease of data collection and ensured a certain degree of internal consistency, it also limited the external validity of the study. As evidenced by some of the studies mentioned in this research, countries may have very different attitudes regarding artificial intelligence, risk perceptions in purchasing situations, and trust dynamics due to several factors, including cultural values and degree of technological maturity (Peña-García et al., 2020; Christodoulides et al., 2012; Abou-Shouk et al., 2024). For the reasons mentioned above, the findings cannot be considered immediately applicable to international contexts, particularly in non-Western areas or countries with lower levels of familiarity with digital tools and new generation technologies.

An additional constraint pertains to the heterogeneity of the sample. Although the inclusion of participants belonging to all genders and various age groups allowed for a global and diversified view regarding the effectiveness of the two sources of recommendation, this diversity may have hidden more subtle and specific effects. For instance, many studies have demonstrated that gender is a key variable in shaping psychological responses to perceived risk, trust and preference for specific sources of information (Prendergast et al., 2016; Doh & Hwang, 2008; Bae & Lee, 2010; Chen et al., 2022; Alizadeh & Kashani, 2024; Islam et al., 2024; Sheehan, 1999). Age also represents a crucial factor, as generally, even looking at the empirical results of this study, younger people tend to exhibit higher degree of openness, understanding and acceptance of AI outputs (Statista, 2023; Chen & Chang, 2018; Alizadeh & Kashani, 2024; Solomovich & Abraham, 2024). Having said this, future research could carry out the same research, applied on more homogeneous and restricted samples (such as women only, individuals over 50, or exclusively digital natives), to examine whether and how these demographic characteristics have a significant impact in determining the perceived effectiveness of the information source in bringing closer consumers to buy.

Moving forward, the experimental design and the nature of the proposed visual stimuli constitute a third limitation of the proposed research. Indeed, to ensure comparability, the recommendation messages, whether produced by human (e-WOM) or artificial sources (ChatGPT) were presented in a textual form and having some features in common, including the tone, length, general layout of the messages and usefulness of the content. However, this standardization introduced a certain degree of artificiality, creating visual scenarios that are not so similar in digital contexts. In real-world scenarios, consumers are impacted by significant contextual factors such as the different content of the recommendation (in turn divided into length, structure and accuracy of the review, presence or absence of images), visual interface or the reputation of the platform. The absence of these multimodal elements may have simplified the process of both designing and responding to the survey, focusing more on the type of recommendation as such rather than on the key elements of each. These graphic characteristics, as already mentioned, limited the external validity of the simulated context. Future studies could incorporate more realistic digital environments, enriched with visual and dynamic stimuli, to better replicate the everyday consumer experience.

The choice of product category also represents a significant constraint. Consumer electronics is a sector typically associated with high cognitive involvement, rational evaluations, high perceived risk, and strong attention to information reliability. This may have influenced the interaction with the sources and the observed outcomes. It is not guaranteed that the same effects would occur in more emotional, hedonic, or impulsive contexts (such as fashion, dining, or tourism) where the dynamics of trust, risk, and credibility assume different characteristics. For this reason, it is advisable that future research replicate this study across different product categories to test the robustness of the conceptual model in alternative consumption contexts.

Another limitation of the study concerns the fact that the psychological dynamics underlying the perceived risk of respondents were not directly measured but rather inferred through mediating variables. Although this approach has been based on several research studies in the existing literature, it leaves broad room for future research for a more in-depth analysis of the mental mechanisms that generate greater risk perception. In this regard, future papers could include more specific metrics related to emotional involvement, social distance, perceived warmth, cognitive and affective trust in the source, to discover any unconscious precursors which may be correlated to the feeling of risk. In an even more insightful and interesting way, these measurements could be made through qualitative tools (interviews, focus groups) or biometric techniques (eye-tracking, physiological measurements), to discover prospects which do not emerge from the purely numerical results of this research.

The high impact of the temporal dimension on the empirical findings should also be considered. In fact, the experiment offers a *snapshot* of the current situation, at a time when AI is quickly developing but still struggling to be understood, accepted, and more particularly to be considered by the average consumer as a reliable information means through which making better informed purchasing choices. At the same time, it is plausible that, over time, technological advancements and users' increased familiarity with platforms such as ChatGPT will alter perceptions of risk and trust, potentially reversing the scenario inferred from this research. It is therefore desirable that future studies track the evolution of AI acceptance and investigate whether and how consumer preferences for this revolutionary tool change over time.

Due to these intrinsic constraints, the present research provides a broad wealth of opportunities to numerous avenues for future investigation. A first natural development could be characterized by the emulation of the study in other cultural contexts, especially in non-Western markets, to observe how cultural variables such as risk aversion, collectivism, or technological maturity influence the relationship between type of information source, consumer trust, and behavioural response.

Secondly, it could represent a noteworthy extension of this paper to consider specific samples, homogeneous in terms of age, gender or other socio-demographic variables, to identify any systematic differences in psychological reactions. A comparison between digital natives and consumers over 60, or between individuals belonging to different income strata, for example, could reveal the existence of demographic variables that have a significant impact on the perception of AI and the effectiveness of human recommendations.

Further development for future investigation is offered by the opportunity to conduct research using alternative visual stimulus formats. Future studies may use voice-based stimuli, or images of known platforms and interfaces, or interactive simulations to assess whether the communication channel affects perceived credibility, emotional commitment and purchase intent. This would also allow researchers to simulate a more realistic buying scenario that is easier for participants to understand.

Furthermore, the integration between human sources and AI is undoubtedly a factor that can be deepened to further extend the findings of this research. Indeed, rather than analysing them separately and treating them as alternatives, future studies could examine hybrid recommendation models. An example of visual stimulus might be displaying ChatGPT which synthesizes human reviews or uses them to comment and compare them with its results. This more dynamic and comprehensive approach could provide new insights into how overlapping and interaction between information sources influence consumers’ purchase intention. For example, researchers may find that regarding product recommendations consumers prefer a mix of the two diverse sources as they meet unique needs and together generate low levels of uncertainty associated to the purchasing process.

In conclusion, although this research offers a valuable contribution to the existing literature, both from a theoretical and managerial point of view, to better figure out the different role of the main sources of information available to the contemporary consumer in reducing risk perception and stimulating purchase intention, it also leaves open a series of issues which future research could address. Deepening the identified limits and developing proposed research scenarios could further enrich the theoretical and practical literature landscape, enabling companies to create marketing, communication, CRM and design techniques which are effective and attractive in the era of convergence between human and artificial intelligence.

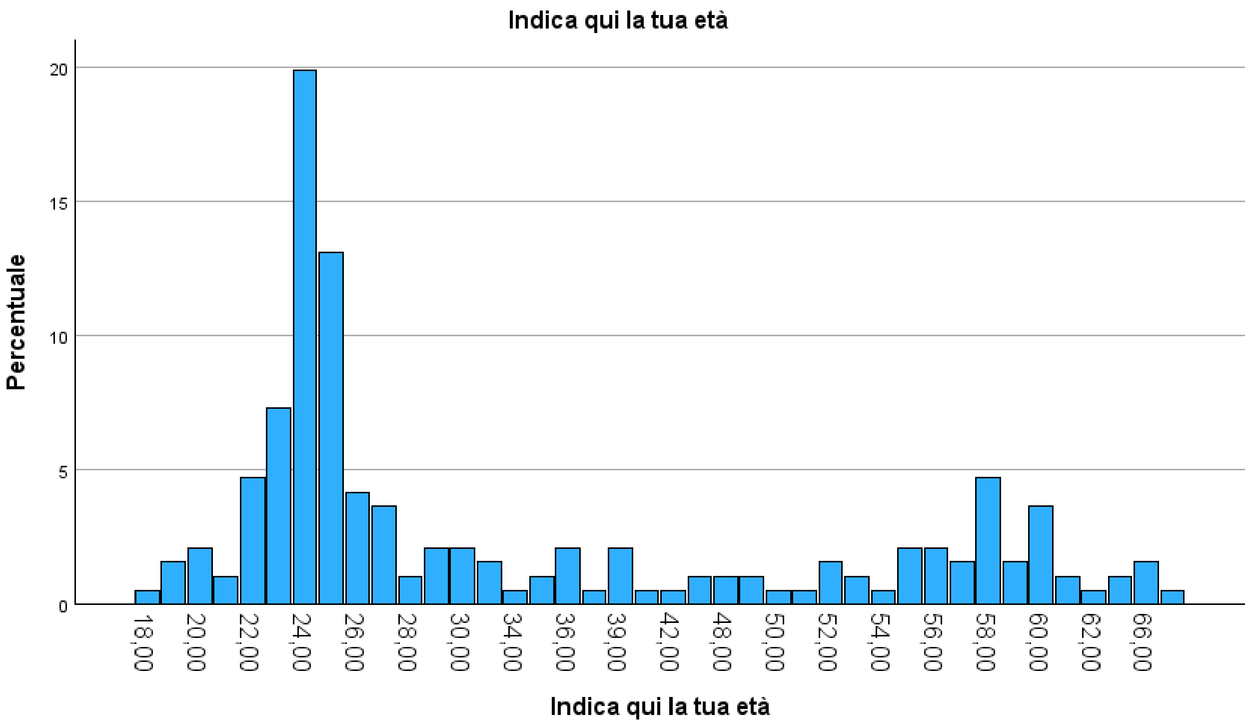
# Appendix

## Descriptive Statistics: Age

**Statistiche**

Indica qui la tua età

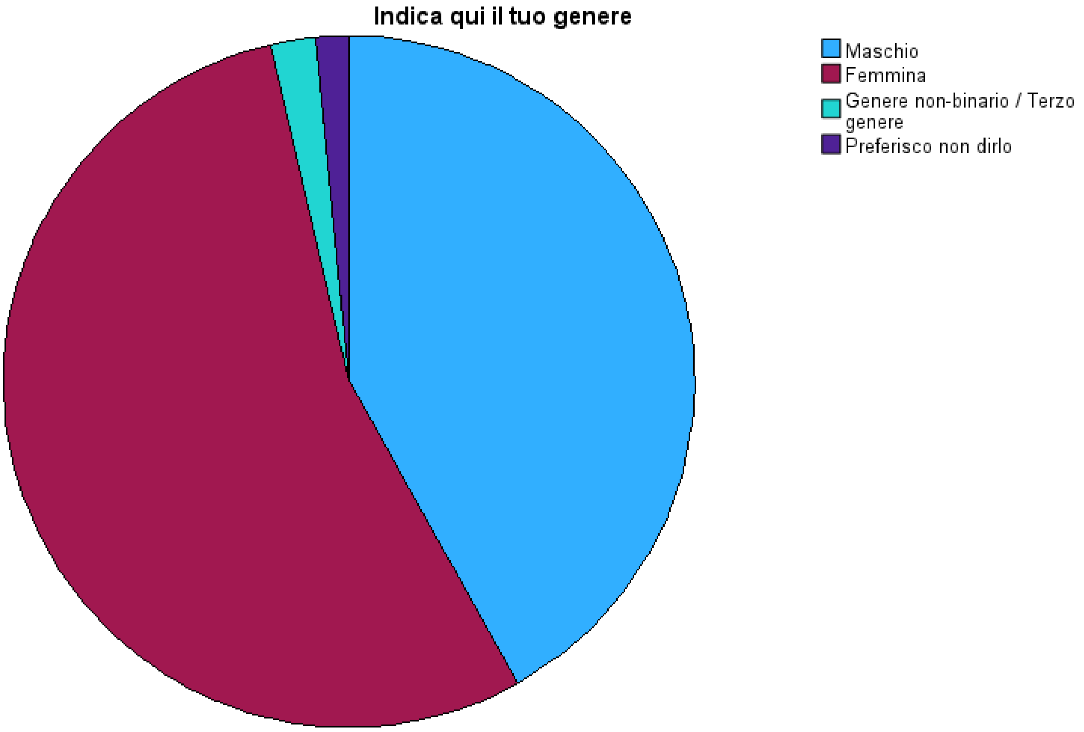
| | | |
|---|---|---|
| N | Valido | 191 |
| | Mancante | 0 |
| Media | | 34,4241 |
| Mediana | | 25,0000 |
| Modalità | | 24,00 |
| Deviazione std. | | 14,72210 |
| Varianza | | 216,740 |
| Intervallo | | 49,00 |
| Minimo | | 18,00 |
| Massimo | | 67,00 |




## Descriptive Statistics: Gender

**Indica qui il tuo genere**

| | | Frequenza | Percentuale | Percentuale valida | Percentuale cumulativa |
|---|---|---|---|---|---|
| Valido | Maschio | 80 | 41,9 | 41,9 | 41,9 |
| | Femmina | 104 | 54,5 | 54,5 | 96,3 |
| | Genere non-binario / Terzo genere | 4 | 2,1 | 2,1 | 98,4 |
| | Preferisco non dirlo | 3 | 1,6 | 1,6 | 100,0 |
| | Totale | 191 | 100,0 | 100,0 | |




## Factorial Analysis: Mediator

**Varianza totale spiegata**

| Componente | Autovalori iniziali | | | Caricamenti somme dei quadrati di estrazione | | |
|---|---|---|---|---|---|---|
| | Totale | % di varianza | % cumulativa | Totale | % di varianza | % cumulativa |
| 1 | 2,627 | 87,550 | 87,550 | 2,627 | 87,550 | 87,550 |
| 2 | ,242 | 8,082 | 95,633 | | | |
| 3 | ,131 | 4,367 | 100,000 | | | |

Metodo di estrazione: Analisi dei componenti principali.

**Comunalità**

| | Iniziale | Estrazione |
|---|---|---|
| Indica su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 1. Fare riferimento alla recensione appena visualizzata è rischioso. | 1,000 | ,881 |
| Indica su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 2. Affidarmi alla recensione appena visualizzata può portare a risultati negativi. | 1,000 | ,907 |
| Indica su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 3. Fare riferimento alla recensione appena visualizzata mi provocherebbe un senso di preoccupazione. | 1,000 | ,838 |

Metodo di estrazione: Analisi dei componenti principali.

**Matrice dei componenti[a]**

| | Componente 1 |
|---|---|
| Indica su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 1. Fare riferimento alla recensione appena visualizzata è rischioso. | ,939 |
| Indica su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 2. Affidarmi alla recensione appena visualizzata può portare a risultati negativi. | ,953 |
| Indica su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 3. Fare riferimento alla recensione appena visualizzata mi provocherebbe un senso di preoccupazione. | ,916 |

Metodo di estrazione: Analisi dei componenti principali.

a. 1 componenti estratti.

**Test di KMO e Bartlett**

| | | |
|---|---|---|
| Misura di Kaiser-Meyer-Olkin di adeguatezza del campionamento. | | ,748 |
| Test della sfericità di Bartlett | Appross. Chi-quadrato | 467,333 |
| | gl | 3 |
| | Sign. | <,001 |

## Reliability Test: Mediator

**Statistiche di affidabilità**

| Alpha di Cronbach | Alpha di Cronbach basata su elementi standardizzati | N. di elementi |
|---|---|---|
| ,928 | ,929 | 3 |

## Factorial Analysis: Dependent Variable

**Varianza totale spiegata**

| Componente | Autovalori iniziali: Totale | Autovalori iniziali: % di varianza | Autovalori iniziali: % cumulativa | Caricamenti somme dei quadrati di estrazione: Totale | Caricamenti somme dei quadrati di estrazione: % di varianza | Caricamenti somme dei quadrati di estrazione: % cumulativa |
|---|---|---|---|---|---|---|
| 1 | 2,754 | 91,792 | 91,792 | 2,754 | 91,792 | 91,792 |
| 2 | ,138 | 4,602 | 96,394 | | | |
| 3 | ,108 | 3,606 | 100,000 | | | |

Metodo di estrazione: Analisi dei componenti principali.

**Comunalità**

| | Iniziale | Estrazione |
|---|---|---|
| Indica su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 1.La probabilità di acquistare uno dei prodotti appena visualizzati è molto alta | 1,000 | ,912 |
| Indica su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 2. La probabilità che io prenda in considerazione l'acquisto di uno dei prodotti appena visualizzati è molto alta | 1,000 | ,928 |
| Indica su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 3. La mia disponibilità ad acquistare uno dei prodotti appena visualizzati è molto alta | 1,000 | ,914 |

Metodo di estrazione: Analisi dei componenti principali.

**Matrice dei componenti**[a]

| | Componente 1 |
|---|---|
| Indica su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 1.La probabilità di acquistare uno dei prodotti appena visualizzati è molto alta | ,955 |
| Indica su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 2. La probabilità che io prenda in considerazione l'acquisto di uno dei prodotti appena visualizzati è molto alta | ,963 |
| Indica su una scala da 1 (completamente in disaccordo) a 7 (completamente d' accordo) in quale misura sei d'accordo o in disaccordo con le seguenti affermazioni. - 3. La mia disponibilità ad acquistare uno dei prodotti appena visualizzati è molto alta | ,956 |

Metodo di estrazione: Analisi dei componenti principali.

a. 1 componenti estratti.

**Test di KMO e Bartlett**

| | | |
|---|---|---|
| Misura di Kaiser-Meyer-Olkin di adeguatezza del campionamento. | | ,776 |
| Test della sfericità di Bartlett | Appross. Chi-quadrato | 600,456 |
| | gl | 3 |
| | Sign. | <,001 |

## Reliability Test: Dependent Variable

**Statistiche di affidabilità**

| Alpha di Cronbach | Alpha di Cronbach basata su elementi standardizzati | N. di elementi |
|---|---|---|
| ,955 | ,955 | 3 |

## One-Way ANOVA: H1

**Descrittive**

DV

| | N | Medio | Deviazione std. | Errore std. | 95% di intervallo di confidenza per la media | | Minimo | Massimo |
|---|---|---|---|---|---|---|---|---|
| | | | | | Limite inferiore | Limite superiore | | |
| ,00 | 96 | 3,4444 | 2,00565 | ,20470 | 3,0381 | 3,8508 | 1,00 | 7,00 |
| 1,00 | 95 | 5,2246 | 1,47832 | ,15167 | 4,9234 | 5,5257 | 1,00 | 7,00 |
| Totale | 191 | 4,3298 | 1,97202 | ,14269 | 4,0484 | 4,6113 | 1,00 | 7,00 |

**ANOVA**

DV

| | Somma dei quadrati | df | Media quadratica | F | Sig. |
|---|---|---|---|---|---|
| Tra gruppi | 151,307 | 1 | 151,307 | 48,669 | <,001 |
| Entro i gruppi | 587,580 | 189 | 3,109 | | |
| Totale | 738,887 | 190 | | | |

**Regression Analysis (Model 4): H2-H3**

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

Sample
Size: 191

**************************************************************************

OUTCOME VARIABLE:
MED

Model Summary

| R | R-sq | MSE | F | df1 | df2 | p |
|---|---|---|---|---|---|---|
| ,4774 | ,2280 | 2,8178 | 55,8053 | 1,0000 | 189,0000 | ,0000 |

Model

| | coeff | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| constant | 4,6007 | ,1713 | 26,8537 | ,0000 | 4,2627 | 4,9386 |
| IV | -1,8147 | ,2429 | -7,4703 | ,0000 | -2,2939 | -1,3355 |

**************************************************************************

OUTCOME VARIABLE:
DV

Model Summary

| R | R-sq | MSE | F | df1 | df2 | p |
|---|---|---|---|---|---|---|
| ,7175 | ,5148 | 1,9069 | 99,7398 | 2,0000 | 188,0000 | ,0000 |

Model

| | coeff | se | t | p | LLCI | ULCI |
|---|---|---|---|---|---|---|
| constant | 6,4618 | ,3093 | 20,8934 | ,0000 | 5,8517 | 7,0719 |
| IV | ,5899 | ,2274 | 2,5937 | ,0102 | ,1413 | 1,0386 |
| MED | -,6559 | ,0598 | -10,9605 | ,0000 | -,7739 | -,5378 |

## References

Bearden William O., Etzel Michael J. (1982). Reference Group Influence on Product and Brand Purchase Decisions. *Journal of Consumer Research*, *9*(2), 183–94.

Bonfield, E. H. (1974). Attitude, Social Influence, Personal Norm, and Intention Interactions as Related to Brand Purchase Behavior. *Journal of Marketing Research*, *11*(4), 379-389.

Ross, I., & Bettman, J. R. (1979). An Information Processing Theory of Consumer Choice. *Journal of Marketing*, *43*(3), 124.

Mittal, B. (2016). The maximizing consumer wants even more choices: How consumers cope with the marketplace of overchoice. *Journal of Retailing and Consumer Services*, *31*, 361–370.

Pütter, M. (2017). The impact of social media on consumer buying intention. *Journal of International Business Research and Marketing*, *3*(1), 7–13.

Brown, J. J., & Reingen, P. H. (1987). Social ties and Word-of-Mouth referral behavior. *Journal of Consumer Research*, *14*(3), 350.

Chatterjee, P. (2001). Online reviews: Do consumers use them? *ACR North American Advances*.

Chevalier, J. A., & Mayzlin, D. (2006). The Effect of Word of Mouth on Sales: Online book reviews. *Journal of Marketing Research*, *43*(3), 345–354.

Hamilton, R., Ferraro, R., Haw s, K. L., & Mukhopadhyay, A. (2021). Traveling with Companions: The Social Customer Journey. *Journal of Marketing*, *85*(1), 68-92.

Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. *Journal of Marketing*, *80*(6), 69–96.

Melnyk, V., Carrillat, F. A., & Melnyk, V. (2021). The Influence of Social Norms on Consumer Behavior: A Meta-Analysis. *Journal of Marketing*, *86*(3), 98–120.

Bearden, W. O., & Rose, R. L. (1990). Attention to social comparison information: an individual difference factor affecting consumer conformity. *Journal of Consumer Research*, *16*(4), 461.

Cascio, C. N., O'Donnell, M. B., Bayer, J., Tinney, F. J., & Falk, E. B. (2015). Neural correlates of susceptibility to group opinions in online Word-of-Mouth recommendations. *Journal of Marketing Research*, *52*(4), 559–575.

Griskevicius Vladas, Kenrick Douglas T. (2013). Fundamental Motives: How Evolutionary Needs Influence Consumer Behavior. *Journal of Consumer Psychology*, *23*(3), 372–86.

Otterbring, T. (2021). Peer presence promotes popular choices: A “Spicy” field study on social influence and brand choice. *Journal of Retailing and Consumer Services*, *61*, 102594.

Goodrich, K., & De Mooij, M. (2013). How ‘social’ are social media? A cross-cultural comparison of online and offline purchase decision influences. *Journal of Marketing Communications*, *20*(1–2), 103–116.

Argo, J. J., & Dahl, D. W. (2020). Social influence in the retail context: a contemporary review of the literature. *Journal of Retailing*, *96*(1), 25-39.

Melumad, S., Hadi, R., Hildebrand, C., & Ward, A. F. (2020). Technology-Augmented Choice: How digital innovations are transforming consumer decision processes. *Customer Needs and Solutions*, *7*(3–4), 90–101.

Court David, Elzinga Dave, Mulder Susan, Vetvik Ole Jorgen (2009). The Consumer Decision Journey. *McKinsey Quarterly* (June). [https://www.mckinsey.com/business-functions/marketing-and-sales/our-insights/the-consumer-decision-journey](https://www.mckinsey.com/business-functions/marketing-and-sales/our-insights/the-consumer-decision-journey).

Scheibehenne, B., Greifeneder, R., & Todd, P. M. (2010). Can there ever be too many options? A meta-analytic review of choice overload. *Journal of Consumer Research*, *37*(3), 409-425.

Banker S., Khetani S. (2019). Algorithm overdependence: How the use of algorithmic recommendation systems can increase risks to consumer well-being. *Journal of Public Policy & Marketing*, *38*(4), 500–515.

Agnihotri, D., Chaturvedi, P., & Tripathi, V. (2024). The impact of social media influencer information overload on purchase avoidance: the role of customer confusion and prior product knowledge. *Journal of Research in Interactive Marketing*.

Chernev, A., Böckenholt, U., & Goodman, J. (2015). Choice overload: A conceptual review and meta-analysis. *Journal of Consumer Psychology*, *25*(2), 333-358.

Lima, A., Cruz, M., & Pacheco, J. (2024). The impact of social media marketing efforts on buying intentions within the brewing sector. *Management & Marketing*, *19*(4), 618–643.

Sridhar, S., & Srinivasan, R. (2012). Social influence effects in online product ratings. *Journal of Marketing*, *76*(5), 70–88.

Kim J., Kim J. H., Kim C., Park J. (2023a). Decisions with ChatGPT: Reexamining choice overload in ChatGPT recommendations. *Journal of Retailing and Consumer Services*, 75, 103494.

Gonçalves, M. J. A., Oliveira, A., Abreu, A., & Mesquita, A. (2024). Social networks and digital influencers in the online purchasing decision process. *Information*, *15*(10), 601.

Aljukhadar, M., Senecal, S., & Daoust, C. (2012). Using Recommendation Agents to Cope with Information Overload. *International Journal of Electronic Commerce*, *17*(2), 41–70.

*Come e perché chiedere recensioni ecommerce ai clienti (2024)*. (2024, November 18). Shopify. https://www.shopify.com/it/blog/recensioni-ecommerce

Deloitte. (2014). *The new digital divide*. https://www2.deloitte.com/content/dam/Deloitte/us/Documents/Tax/us-rd-thenewdigitaldivide-041814.pdf

Quinn, W., & Quinn, W. (2022, July 21). *Beyond martech: building trust with consumers and engaging where sentiment is high*. Nielsen. https://www.nielsen.com/insights/2021/beyond-martech-building-trust-with-consumers-and-engaging-where-sentiment-is-high/

Ahern, G. (2022, November 15). *Chatbot Survey – How does a chatbot do market research?* Ometrics. https://www.ometrics.com/blog/chatbot-survey-how-does-a-chatbot-do-market-research

Fokina, M. (2024, October 18). *The Future of Chatbots: 80+ Chatbot statistics for 2025*. Tidio. https://www.tidio.com/blog/chatbot-statistics/

Bughin, J., Doogan, J., & Vetvik, O. J. (2010, April 1). *A new way to measure word-of-mouth marketing*. McKinsey & Company. https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/a-new-way-to-measure-word-of-mouth-marketing

Baer, J. (2014, August 9). *The 8 things Online Influencers can do for you* [Slide show]. SlideShare. https://www.slideshare.net/slideshow/8-things-online-influencers-can-do-for-you/37832657#3

Pr, T. (2023, September 14). New Study Finds Majority of Millennials Distrust All Forms of Advertising, But Close Friends, Digital Channels, Even Online News Sources Rank as Most Trustworthy. *Unknown Journal*. https://www.prweb.com/releases/new_study_finds_majority_of_millennials_distrust_all_forms_of_advertising_but_close_friends_digital_channels_even_online_news_sources_rank_as_most_trustworthy/prweb11870392.htm

*Top 22 benefits of chatbots for businesses and customers*. (2025, May 22). Zendesk. https://www.zendesk.com/blog/5-benefits-using-ai-bots-customer-service/

Curran, N. (2025, February 10). Brands that don't sell via social media are missing out. *The Times*. https://www.thetimes.com/business-money/entrepreneurs/article/brands-that-dont-sell-via-social-media-are-missing-out-enterprise-network-wzbbz87pq

Balkhi, S. (2025, January 10). *60+ Statistiche sull'Influencer Marketing che dovreste conoscere (2025)*. WPBeginner. https://www.wpbeginner.com/it/research/influencer-marketing-statistics/

Wong, B., JD. (2023, May 18). *Top social media statistics and trends*. Forbes Advisor. https://www.forbes.com/advisor/business/social-media-statistics/#source

Statista. (n.d.). *Influencer Advertising - Worldwide | Market Forecast*. https://www.statista.com/outlook/amo/advertising/influencer-advertising/worldwide

Mucci, T. (2025, April 17). History of artificial intelligence. *IBM*. https://www.ibm.com/think/topics/history-of-artificial-intelligence

MacKenzie, I., Meyer, C., & Noble, S. (2013, October 1). *How retailers can keep up with consumers*. McKinsey & Company. https://www.mckinsey.com/industries/retail/our-insights/how-retailers-can-keep-up-with-consumers#

*What is personalization?* (2023, May 30). McKinsey & Company. https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-personalization

*Topic: Word-of-mouth (WOM) marketing and advertising*. (2024, June 26). Statista. https://www.statista.com/topics/12485/word-of-mouth-wom-marketing-and-advertising/#topicOverview

Strategies, P. (2017, May 25). *Il passaparola: come rendere contagioso un prodotto - Performance Strategies*. Performance Strategies. https://www.performancestrategies.it/marketing-e-comunicazione/il-passaparola-come-rendere-contagioso-un-prodotto/

Steck, H., Baltrunas, L., Elahi, E., Liang, D., Raimond, Y., & Basilico, J. (2021). Deep learning for recommender systems: A Netflix case study. *AI Magazine*, *42*(3), 7–18.

Lebow, S. (2023, November 30). *Product research is the leading use for AI chatbots in shopping*. EMARKETER. https://www.emarketer.com/content/product-research-leading-use-ai-chatbots-shopping

Mogaji, E., & Jain, V. (2024). How generative AI is (will) change consumer behaviour: Postulating the potential impact and implications for research, practice, and policy. *Journal of Consumer Behaviour*, *23*(5), 2379–2389.

Hermann, E., & Puntoni, S. (2024). Artificial intelligence and consumer behavior: From predictive to generative AI. *Journal of Business Research*, *180*, 114720.

Jan, I. U., Ji, S., & Kim, C. (2023). What (de) motivates customers to use AI-powered conversational agents for shopping? The extended behavioral reasoning perspective. *Journal of Retailing and Consumer Services*, *75*, 103440.

Wong, I. A., Lian, Q. L., & Sun, D. (2023). Autonomous travel decision-making: An early glimpse into ChatGPT and generative AI. *Journal of Hospitality and Tourism Management*, *56*, 253–263.

Kumar, A., Shankar, A., Behl, A., Chakraborty, D., & Gundala, R. R. (2025). Anthropomorphic generative AI chatbots for enhancing customer engagement, experience and recommendation. *Journal of Consumer Marketing*.

Gupta, A. S., & Mukherjee, J. (2025). Framework for adoption of generative AI for information search of retail products and services. *International Journal of Retail & Distribution Management*, *53*(2), 165-181.

Tilawat, M. (2025, May 7). *Statistiche degli agenti di intelligenza artificiale nel 2025: Impatto sul mercato e prospettive del settore*. All About AI. https://www.allaboutai.com/it-it/agenti-ia/statistiche/

Statista. (2024, April 5). *Shoppers using generative-AI tools for recommendations 2023, by generation*. https://www.statista.com/statistics/1380351/gen-ai-for-product-recommendations-by-generation/

*Il 71% dei consumatori vorrebbe che l'AI generativa fosse integrata nelle proprie esperienze d'acquisto - Capgemini Italia*. (2025, January 24). Capgemini Italia. https://www.capgemini.com/it-it/news/comunicati-stampa/il-71-dei-consumatori-vorrebbe-che-lai-generativa-fosse-integrata-nelle-proprie-esperienze-dacquisto/

https://www.reuters.com/business/retail-consumer/ai-influenced-shopping-boosts-online-holiday-sales-salesforce-data-shows-2025-01-06/

Morgan, J. (n.d.). *The rise of Generative AI | J.P. Morgan Research*. https://www.jpmorgan.com/insights/global-research/artificial-intelligence/generative-ai

Cialdini, R. B., & Trost, M. R. (1998). Social influence: Social norms, conformity and compliance.

Bhukya, R., & Paul, J. (2023). Social influence research in consumer behavior: What we learned and what we need to learn? – A hybrid systematic literature review. *Journal of Business Research*, *162*, 113870.

Kirmani, A., & Ferraro, R. (2017). Social influence in marketing: how other people influence consumer information processing and decision making. *The Oxford handbook of social influence*, *1*, 415-432.

Gunawan, C. M., Rahmania, L., & Kenang, I. H. (2023). The influence of social influence and peer influence on intention to purchase in e-commerce. *Review of Management and Entrepreneurship*, *7*(1), 61-84.

Zhou, L., & Wong, A. (2008). Exploring the influence of product conspicuousness and social compliance on purchasing motives of young Chinese consumers for foreign brands. *Journal of Consumer Behaviour*, *7*(6), 470–483.

D'Angelo J. K., Diehl K., Cavanaugh L. A. (2019). Lead by example? Custom-made examples created by close others lead consumers to make dissimilar choices. *Journal of Consumer Research*, *46*(4), 750–773.

Escalas, J. E., & Bettman, J. R. (2003). You are what they eat: The influence of reference groups on consumers' connections to brands. *Journal of Consumer Psychology*, *13*(3), 339–348.

White, K., & Simpson, B. (2012). When do (and don't) normative appeals influence sustainable consumer behaviors? *Journal of Marketing*, *77*(2), 78–95.

Zong, Z., Liu, X., & Gao, H. (2023). Exploring the mechanism of consumer purchase intention in a traditional culture based on the theory of planned behavior. *Frontiers in Psychology*, *14*.

Clark, T., & Eckhardt, G. (2003). Book Review: Culture's Consequences: Comparing Values, Behaviors, Institutions and Organizations across Nations, 2d ed. *Journal of Marketing*, *67*(2), 151–153.

Jakubanecs, A., Supphellen, M., Helgeson, J. G., Haugen, H. M., & Sivertstøl, N. (2022). The impact of cultural variability on brand stereotype, emotion and purchase intention. *Journal of Consumer Marketing*, *40*(1), 112–123.

Jin, H., & Wang, H. (2017). A Study on the Influence of Teenagers' Personal Characteristics in Family Purchase Decision. *Advances in Social Science, Education and Humanities Research*.

Singh, R., & Nayak, J. (2014). Peer Interaction and Its Influence on Family Purchase Decision: A Study among Indian Teenagers. *Vision the Journal of Business Perspective*, *18*(2), 81–90.

Zhang, X., Li, S., Burke, R. R., & Leykin, A. (2014). An examination of social influence on shopper behavior using video tracking data. *Journal of Marketing*, *78*(5), 24–41.

Wang, X., Yu, C., & Wei, Y. (2012). Social Media peer communication and Impacts on purchase Intentions: A Consumer Socialization framework. *Journal of Interactive Marketing*, *26*(4), 198–208.

Childers, T. L., & Rao, A. R. (1992). The influence of familial and Peer-Based reference groups on consumer decisions. *Journal of Consumer Research*, *19*(2), 198.

Harwanto, H., Nuari, N. R., & Christian, P. (2020). The effect of brand image, Variety-Seeking tendency, and peer influence to promotional activity interest and its effect to purchase intention on millennials. *International Journal of Research*, *7*(2), 208–213.

The effect of brand image, Variety-Seeking tendency, and peer influence to promotional activity interest and its effect to purchaseintention on millennials. (2020). In *International Journal of Research and Review* (Vol. 7, Issue 2, pp. 208–209). https://www.ijrrjournal.com/IJRR_Vol.7_Issue.2_Feb2020/IJRR0033.pdf

Khan, H. A., Kamal, Y., & Saleem, S. (2016). Peer influence on young adults' products purchase decisions. *Business & Economic Review*, *8*(Special Edition), 83–92.

RV, S., & Varshney, S. (2022). Investigating combined effect of WOM and eWOM: role of message valence. *Journal of Consumer Marketing*, *39*(2), 180–190.

Cruz, M., Silva, S. C. E., & Machado, J. C. (2017). The influence of WOM and Peer Interaction in the Decision-Making Process of Generation Z within the family. *International Journal of Marketing Communication and New Media*, *2*.

De Matos, C. A., & Rossi, C. A. V. (2008). Word-of-mouth communications in marketing: a meta-analytic review of the antecedents and moderators. *Journal of the Academy of marketing science*, *36*, 578-596.

Westbrook, R. A. (1987). Product/Consumption-Based affective responses and postpurchase processes. *Journal of Marketing Research*, *24*(3), 258–270.

Walsh, G., & Mitchell, V. (2010). The effect of consumer confusion proneness on word of mouth, trust, and customer satisfaction. *European Journal of Marketing*, *44*(6), 838–859.

Huete-Alcocer, N. (2017). A Literature review of Word of Mouth and Electronic Word of Mouth: Implications for Consumer Behavior. *Frontiers in Psychology*, *8*.

Meiners, N. H., Schwarting, U., & Seeberger, B. (2010). The Renaissance of Word-of-Mouth Marketing: A "New" standard in Twenty-First Century Marketing management?! *International Journal of Business and Economic Sciences Applied Research*, *3*(2), 79–97.

Rosen, E. (2001). The anatomy of buzz: how to create word-of-mouth marketing. *Cornell Hotel and Restaurant Administration Quarterly*, *42*(3), 7.

Haenlein, M., & Libai, B. (2017). Seeding, referral, and recommendation. *California Management Review, 59*(2), 68–91.

Trusov, M., Bucklin, R. E., & Pauwels, K. (2009). Effects of Word-of-Mouth versus Traditional Marketing: Findings from an Internet Social Networking Site. *Journal of Marketing*, *73*(5), 90–102.

Hogan, J. E., Lemon, K. N., & Libai, B. (2004). Quantifying the ripple: Word-of-Mouth and advertising effectiveness. *Journal of Advertising Research*, *44*(3), 271–280.

McCarthy, J. (2004). *What is Artificial Intelligence?* Stanford University.

Villanueva, J., Yoo, S., & Hanssens, D. M. (2008). The Impact of Marketing-Induced Versus Word-of-Mouth Customer Acquisition on Customer Equity Growth. *Journal of Marketing Research*, *45*(1), 48–59.

Faraji-Rad A., Samuelsen B. M., Warlop L. (2015). On the persuasiveness of similar others: The role of mentalizing and the feeling of certainty. *Journal of Consumer Research*, *42*(3), 458–471.

Mann, M. F., & Hill, T. (1984). Persuasive Communications and the Boomerang Effect: Some Limiting Conditions to the Effectiveness of Positive Influence Attempts. *Advances in Consumer Research*, *11*(1).

Gupta, S., & Chundawat, D. S. (2002). Family and social influences in buying Decision making - A study of Refrigerator. *NMIMS Management Review*, *14*(2), 31–41.

Fitzsimons, G. J., & Lehmann, D. R. (2004). Reactance to recommendations: When unsolicited advice yields contrary responses. *Marketing Science*, *23*(1), 82–94.

Zirena-Bejarano, P. P., & Zirena, E. M. C. (2024). From Consumer's Attitude towards Online Purchase Decision: Influence of Friends and Reference Groups. *Contemporary Management Research*, *20*(1), 1–24.

Zhao, M., & Xie, J. (2011). Effects of social and temporal distance on consumers' responses to peer recommendations. *Journal of Marketing Research*, *48*(3), 486–496.

Duhan, D. F., Johnson, S. D., Wilcox, J. B., & Harrell, G. D. (1997). Influences on consumer use of Word-of-Mouth recommendation sources. *Journal of the Academy of Marketing Science*, *25*(4), 283–295.

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the Internet? *Journal of Interactive Marketing*, *18*(1), 38–52.

Haq, M. D., Tseng, T., Cheng, H., & Chiu, C. (2024). An empirical analysis of eWOM valence effects: Integrating stimulus-organism-response, trust transfer theory, and theory of planned behavior perspectives. *Journal of Retailing and Consumer Services*, *81*, 104026.

Sulthana, A.N., & Vasantha, S. (2019). Influence of electronic word of mouth eWOM on purchase intention. *International Journal of Scientific and Technology Research, 8*(10), 1-5.

Roy, G., Datta, B., & Basu, R. (2017). Effect of eWOM valence on online retail sales. *Global Business Review*, *18*(1), 198–209.

Buttle, F. A. (1998). Word of mouth: understanding and managing referral marketing. *Journal of Strategic Marketing*, *6*(3), 241–254.

Moe, W. W., & Trusov, M. (2011). The value of social dynamics in online product ratings forums. *Journal of Marketing Research*, *48*(3), 444–456.

Chen, C., Nguyen, B., Klaus, P. "., & Wu, M. (2015). Exploring Electronic Word-of-Mouth (eWOM) in The Consumer Purchase Decision-Making Process: The Case of Online Holidays – Evidence from United Kingdom (UK) Consumers. *Journal of Travel & Tourism Marketing*, *32*(8), 953–970.

Kour, M., Kaur, R., Bhullar, A., Chaudhary, R., & Siddiqui, A. (2024). Identifying the relationship between e-WOM engagement factors and users' purchase intention through social commerce. *International Journal of Electronic Marketing and Retailing*, *16*(1), 79–103.

Yang, X. (2022). Consumers' purchase intentions in social commerce: the role of social psychological distance, perceived value, and perceived cognitive effort. *Information Technology and People*, *35*(8), 330–348.

Zhu, R., Dholakia, U. M., Chen, X., & Algesheimer, R. (2012). Does online community participation foster risky financial behavior? *Journal of Marketing Research*, *49*(3), 394–407.

Fu, J., Lu, I., Chen, J. H., & Farn, C. (2020). Investigating consumers' online social shopping intention: An information processing perspective. *International Journal of Information Management*, *54,* 102189.

Sharma, R. S., Morales-Arroyo, M., & Pandey, T. (2011). The emergence of electronic Word-of-Mouth as a marketing channel for the digital marketplace. *Journal of Information Information Technology and Organizations (Years 1-3)*, *6,* 041–061.

Dwivedi, Y. K., Kapoor, K. K., & Chen, H. (2015). Social media marketing and advertising. *The Marketing Review*, *15*(3), 289–309.

Ansari, S., Ansari, G., Ghori, M. U., & Kazi, A. G. (2019). Impact of brand awareness and social media content marketing on consumer purchase decision. *Journal of Public Value and Administrative Insight*, *2*(2), 5–10.

Khanom, M. T. (2023). Using social media marketing in the digital era: A necessity or a choice. *International Journal of Research in Business and Social Science (2147-4478)*, *12*(3), 88–98.

Kaplan, A. M., & Haenlein, M. (2009). Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons*, *53*(1), 59–68.

Gunawan, D. D., Huarng, K. H. (2015). Viral effects of social network and media on consumers' purchase intention. *Journal of Business Research*, 68(10), 2235-2244.

Zhu, F., & Zhang, X. (2010). Impact of Online consumer reviews on sales: The moderating role of product and consumer characteristics. *Journal of Marketing*, *74*(2), 133–148.

Bartschat, M., Cziehso, G., & Hennig-Thurau, T. (2021). Searching for word of mouth in the digital age: Determinants of consumers' uses of face-to-face information, internet opinion sites, and social media. *Journal of Business Research*, *141*, 393–409.

Huang, W., Wang, X., Zhang, Q., Han, J., & Zhang, R. (2025). Beyond likes and comments: How social proof influences consumer impulse buying on short-form video platforms. *Journal of Retailing and Consumer Services*, *84*, 104199.

Erkan, I., & Evans, C. (2016). The influence of eWOM in social media on consumers' purchase intentions: An extended approach to information adoption. *Computers in human behavior*, *61*, 47-55.

Ismagilova, E., Slade, E. L., Rana, N. P., & Dwivedi, Y. K. (2019). The Effect of Electronic word of mouth communications on Intention to Buy: A Meta-Analysis. *Information Systems Frontiers*, *22*(5), 1203–1226.

Zangeneh, S. K., Rezvani, M., & Mohammadkazemi, R. (2014). Investigating the effect of Electronic Word Of Mouth on customer's purchase intention of digital products. *Management Science Letters*, *4*(11), 2433–2440.

De Bruyn, A., & Lilien, G. L. (2008). A multi-stage model of word-of-mouth influence through viral marketing. *International Journal of Research in Marketing*, *25*(3), 151–163.

De Langhe, B., Fernbach, P. M., & Lichtenstein, D. R. (2015). Navigating by the Stars: Investigating the actual and perceived validity of online user ratings. *Journal of Consumer Research*, *42*(6), 817–833.

Roy, G., Datta, B., & Mukherjee, S. (2018). Role of electronic word-of-mouth content and valence in influencing online purchase behavior. *Journal of Marketing Communications*, *25*(6), 661–684.

Filieri, R., & McLeay, F. (2013). E-WOM and accommodation. *Journal of Travel Research*, *53*(1), 44–57.

Zhang, K. Z., Zhao, S. J., Cheung, C. M., & Lee, M. K. (2014). Examining the influence of online reviews on consumers' decision-making: A heuristic–systematic model. *Decision support systems*, *67*, 78-89.

Cao, Q., Duan, W., & Gan, Q. (2010). Exploring determinants of voting for the "helpfulness" of online user reviews: A text mining approach. *Decision Support Systems*, *50*(2), 511–521.

Lee, E., & Shin, S. Y. (2013). When do consumers buy online product reviews? Effects of review quality, product type, and reviewer's photo. *Computers in Human Behavior*, *31*, 356–366.

Leong, C., Loi, A. M., & Woon, S. (2021). The influence of social media eWOM information on purchase intention. *Journal of Marketing Analytics*, *10*(2), 145–157.

Majumder, M. G., Gupta, S. D., & Paul, J. (2022). Perceived usefulness of online customer reviews: A review mining approach using machine learning & exploratory data analysis. *Journal of Business Research*, *150*, 147–164.

Cheng, Y. H., & Ho, H. Y. (2015). Social influence's impact on reader perceptions of online reviews. *Journal of Business Research*, *68*(4), 883-887.

Filieri, R. (2014). What makes online reviews helpful? A diagnosticity-adoption framework to explain informational and normative influences in e-WOM. *Journal of Business Research*, *68*(6), 1261–1270.

Donthu, N., Kumar, S., Pandey, N., Pandey, N., & Mishra, A. (2021). Mapping the electronic word-of-mouth (eWOM) research: A systematic review and bibliometric analysis. *Journal of Business Research*, *135*, 758-773.

Prendergast, G., Paliwal, A., & Chan, K. K. F. (2016). Trust in online recommendations: an evolutionary psychology perspective. *International Journal of Advertising*, *37*(2), 199–216.

Doh, S., & Hwang, J. (2008). How consumers Evaluate eWOM (Electronic Word-of-Mouth) Messages. *CyberPsychology & Behavior*, *12*(2), 193–197.

Ali, Z. S., & Cai, H. L. (2022). Who decides where to go for a coffee? E-WOM and consumers' purchase intention. *Journal of Marketing Strategies*, *4*(1), 24–58.

Babić Rosario, A., Sotgiu, F., De Valck, K., & Bijmolt, T. H. (2016). The effect of electronic word of mouth on sales: A meta-analytic review of platform, product, and metric factors. *Journal of Marketing Research*, *53*(3), 297-318.

Kim, K., Yoon, S., & Choi, Y. K. (2018). The effects of eWOM volume and valence on product sales – an empirical examination of the movie industry. *International Journal of Advertising*, *38*(3), 471–488.

Bickart, B., & Schindler, R. M. (2001). Internet forums as influential sources of consumer information. *Journal of Interactive Marketing*, *15*(3), 31–40.

Helm, S. (2000). Viral Marketing - Establishing customer relationships by "Word-of-mouse." *Electronic Markets*, *10*(3), 158–161.

Chen, J., Teng, L., Yu, Y., & Yu, X. (2015). The effect of online information sources on purchase intentions between consumers with high and low susceptibility to informational influence. *Journal of Business Research*, *69*(2), 467–475.

Vrontis, D., Makrides, A., Christofi, M., & Thrassou, A. (2021). Social media influencer marketing: A systematic review, integrative framework and future research agenda. *International Journal of Consumer Studies*, *45*(4), 617-644.

Lima, A., Cruz, M., & Pacheco, J. (2024). The impact of social media marketing efforts on buying intentions within the brewing sector. *Management & Marketing*, *19*(4), 618–643.

Weinberg, T. (2009). The new community rules: Marketing on the social web.

Meliawati, T., Gerald, S. C., & Aruman, N. a. E. (2023). The effect of social media marketing TikTok and product quality towards purchase intention. *Journal of Consumer Sciences*, *8*(1), 77–92.

Kim, A. J., & Ko, E. (2010). Impacts of luxury fashion brand's social media marketing on customer relationship and purchase intention. *Journal of Global Fashion Marketing*, *1*(3), 164–171.

Ye, G., Hudders, L., De Jans, S., & De Veirman, M. (2021). The Value of Influencer Marketing for Business: A bibliometric analysis and managerial implications. *Journal of Advertising*, *50*(2), 160–178.

Chetioui, Y., Benlafqih, H., & Lebdaoui, H. (2020). How fashion influencers contribute to consumers' purchase intention. *Journal of Fashion Marketing and Management*, *24*(3), 361–380.

Almohaimmeed, B. M. A. (2019). The effects of social media Marketing antecedents on social media marketing, brand loyalty and purchase intention: A Customer perspective. *Journal of Business & Retail Management Research*, *13*(04).

Balakrishnan, B. K., Dahnil, M. I., & Yi, W. J. (2014). The Impact of Social Media Marketing Medium toward Purchase Intention and Brand Loyalty among Generation Y. *Procedia - Social and Behavioral Sciences*, *148*, 177–185.

Laksamana, P. (2018). Impact of Social Media Marketing on Purchase Intention and Brand Loyalty: Evidence from Indonesia's Banking Industry. *International Review of Management and Marketing*, *8*(1), 13–18.

Husnain, M., & Toor, A. (2017). The impact of social network marketing on consumer purchase intention in Pakistan: Consumer Engagement as a Mediator. *Asian Journal of Business and Accounting*, *10*(1), 167–199.

Moslehpour, M., Ismail, T., Purba, B., & Wong, W. (2021). What makes GO-JEK go in Indonesia? The influences of social media marketing activities on purchase intention. *Journal of Theoretical and Applied Electronic Commerce Research*, *17*(1), 89–103.

Hanaysha, J. R. (2022). Impact of social media marketing features on consumer's purchase decision in the fast-food industry: Brand trust as a mediator. *International Journal of Information Management Data Insights*, *2*(2), 100102.

Sanny, L., Arina, A. N., Maulidya, R. T., & Pertiwi, R. P. (2020). Purchase intention on Indonesia male's skin care by social media marketing effect towards brand image and brand trust. *Management Science Letters*, 2139–2146.

Ceyhan, A. (2019). The impact of perception related social media marketing applications on consumers' brand loyalty and purchase intention. *EMAJ Emerging Markets Journal*, *9*(1), 88–100.

Nawaz, S. S., & Kaldeen, M. (2020). Impact of digital marketing on purchase intention. *International Journal of Advanced Science and Technology*, *29*(4), 1113-1120.

Güngör, A. S., Çadırcı, T. O., Köse, Ş. G., & Çizer, E. Ö. (2024). Consumer responses toward smart technology: A systematic review, synthesis, and future research agenda. *International Journal of Consumer Studies*, *48*(3).

Alalwan, A. A. (2018). Investigating the impact of social media advertising features on customer purchase intention. *International Journal of Information Management*, *42*, 65–77.

Müller, L. K., Mattke, J., & Maier, C. (2018). #Sponsored #Ad: Exploring the Effect of Influencer Marketing on Purchase Intention.

Babu, E., Joseph, N. M., & Aboobaker, N. (2024). Unveiling the Impact of Influencer Attributes on Purchase Intention of Gen Z: The Moderating Role of Parasocial Interaction. *Global Business Review*, 09721509241280996.

Hermanda, A., Sumarwan, U., & Tinaprillia, N. (2019). The effect of social media influencer on brand image, self-concept, and purchase intention. *Journal of Consumer Sciences*, *4*(2), 76-89.

Koay, K. Y., Cheah, C. W., & Goon, S. W. U. (2023). How do perceived social media marketing activities foster purchase intentions? A multiple sequential mediation model. *Journal of Global Marketing*, *36*(3), 210-224.

Leung, F. F., Gu, F. F., Li, Y., Zhang, J. Z., & Palmatier, R. W. (2022). Influencer marketing effectiveness. *Journal of Marketing*, *86*(6), 93–115.

Li, Y., & Peng, Y. (2021). Influencer marketing: purchase intention and its antecedents. *Marketing Intelligence & Planning*, *39*(7), 960–978.

Koay, K. Y., Cheung, M. L., Soh, P. C., & Teoh, C. W. (2021). Social media influencer marketing: the moderating role of materialism. *European Business Review*, *34*(2), 224–243.

Lim, X. J., Radzol, A. R. B. M., Cheah, J., & Wong, M. W. (2017). The impact of social media influencers on purchase intention and the mediation effect of customer attitude. *Asian Journal of Business Research*, *7*(2).

Sokolova, K., & Kefi, H. (2019). Instagram and YouTube bloggers promote it, why should I buy? How credibility and parasocial interaction influence purchase intentions. *Journal of Retailing and Consumer Services*, *53*, 101742.

Duffek, B., Eisingerich, A. B., Merlo, O., & Lee, G. (2025). EXPRESS: Authenticity in Influencer Marketing: How Can Influencers and Brands Work Together to Build and Maintain Influencer Authenticity? *Journal of Marketing*, 00222429251319786.

Kay, S., Mulcahy, R., & Parkinson, J. (2020). When less is more: the impact of macro and micro social media influencers' disclosure. *Journal of Marketing Management*, *36*(3–4), 248–278.

Tiwari, A., Kumar, A., Kant, R., & Jaiswal, D. (2024). Impact of fashion influencers on consumers' purchase intentions: Theory of planned behaviour and mediation of attitude. *Journal of Fashion Marketing and Management*, *28*(2), 209-225.

Harison, E., & Lahav, Y. (2024). The Impact of Social Media Influencers on Women's Online Purchasing Decisions: An Exploratory Study. In *New Trends in Marketing and Consumer Science* (pp. 372-386). IGI Global.

Saima, N., & Khan, M. A. (2020). Effect of social media influencer marketing on consumers' purchase intention and the mediating role of credibility. *Journal of Promotion Management*, *27*(4), 503–523.

Yuan, S., & Lou, C. (2020b). How Social Media Influencers Foster Relationships with Followers: The Roles of Source Credibility and Fairness in Parasocial Relationship and Product Interest. *Journal of Interactive Advertising*, *20*(2), 133–147.

Jansom, A., & Pongsakornrungsilp, S. (2021). How Instagram influencers affect the value perception of Thai millennial followers and purchasing intention of luxury fashion for sustainable marketing. *Sustainability*, *13*(15), 8572.

Bhagat, S., Khanna, S., Sharma, P., & Bhat, D. A. R. (2024). Street food in the digital era: unraveling the influence of food vloggers credibility and information quality on consumer intentions. *International Journal of Social Economics*.

Weismueller, J., Harrigan, P., Wang, S., & Soutar, G. N. (2020). Influencer Endorsements: How advertising disclosure and source credibility affect consumer purchase intention on social media. *Australasian Marketing Journal (AMJ)*, *28*(4), 160–170.

Sinha, P., Shastri, A., & Lorimer, S. (2023, March 31). *How Generative AI will change sales*. Harvard Business Review. https://hbr.org/2023/03/how-generative-ai-will-change-sales

Haenlein, M., & Kaplan, A. (2019). A Brief History of artificial intelligence: on the past, present, and future of artificial intelligence. *California Management Review*, *61*(4), 5–14.

Chintalapati, S., & Pandey, S. K. (2021). Artificial intelligence in marketing: A systematic literature review. *International Journal of Market Research*, *64*(1), 38–68.

Kumar, V., Rajan, B., Venkatesan, R., & Lecinski, J. (2019). Understanding the Role of Artificial Intelligence in Personalized Engagement Marketing. *California Management Review*, *61*(4), 135-155.

Harkness, L., Robinson, K., Stein, E., & Wu, W. (2023, December 5). How generative AI can boost consumer marketing. *McKinsey & Company*. https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/how-generative-ai-can-boost-consumer-marketing#/

De Bruyn, A., Viswanathan, V., Beh, Y. S., Brock, J. K. U., & Von Wangenheim, F. (2020). Artificial intelligence and marketing: Pitfalls and opportunities. *Journal of Interactive Marketing*, *51*(1), 91-105.

Davenport, T., Guha, A., Grewal, D., & Bressgott, T. (2019). How artificial intelligence will change the future of marketing. *Journal of the Academy of Marketing Science*, *48*(1), 24–42.

Chen, C., Tian, A. D., & Jiang, R. (2024). When Post Hoc Explanation Knocks: Consumer Responses to Explainable AI Recommendations. *Journal of Interactive Marketing*, *59*(3), 234-250.

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2014). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology General*, *144*(1), 114–126.

Kozinets, R. V., & Gretzel, U. (2020). Commentary: Artificial intelligence: The Marketer’s dilemma. *Journal of Marketing*, *85*(1), 156–159.

Aksoy, L., Cooil, B., & Lurie, N. H. (2011). Decision quality measures in Recommendation Agents research. *Journal of Interactive Marketing*, *25*(2), 110–122.

Aksoy, L., Bloom, P. N., Lurie, N. H., & Cooil, B. (2006). Should recommendation agents think like people? *Journal of Service Research*, *8*(4), 297–315.

Nilashi, M., Jannach, D., bin Ibrahim, O., Esfahani, M. D., & Ahmadi, H. (2016). Recommendation quality, transparency, and website quality for trust-building in recommendation agents. *Electronic Commerce Research and Applications*, *19*, 70-84.

Kim, T. W., & Duhachek, A. (2020). Artificial intelligence and persuasion: A construal-level account. *Psychological Science*, *31*(4), 363-380.

Longoni, C., & Cian, L. (2020). Artificial Intelligence in Utilitarian vs. Hedonic Contexts: The “Word-of-Machine” Effect. *Journal of Marketing*, *86*(1), 91–108.

Glikson, E., & Woolley, A. W. (2020). Human trust in artificial intelligence: Review of empirical research. *Academy of Management Annals*, *14*(2), 627-660.

Dietvorst, B. J., & Bharti, S. (2020). People reject algorithms in uncertain decision domains because they have diminishing sensitivity to forecasting error. *Psychological science*, *31*(10), 1302-1314.

Xie, Z., Yu, Y., Zhang, J., & Chen, M. (2022). The searching artificial intelligence: Consumers show less aversion to algorithm-recommended search product. *Psychology and Marketing*, *39*(10), 1902–1919. https://doi.org/10.1002/mar.21706

Ahn, J., Kim, J., & Sung, Y. (2021). The effect of gender stereotypes on artificial intelligence recommendations. *Journal of Business Research*, *141*, 50–59.

Borau, S., Otterbring, T., Laporte, S., & Wamba, S. F. (2021). The most human bot: Female gendering increases humanness perceptions of bots and acceptance of AI. *Psychology and Marketing*, *38*(7), 1052–1068.

Blut, M., Wang, C., Wünderlich, N. V., & Brock, C. (2021). Understanding anthropomorphism in service provision: a meta-analysis of physical robots, chatbots, and other AI. *Journal of the Academy of Marketing Science*, *49*(4), 632–658.

Greiner, D., & Lemoine, J. (2025). Bridging the gap: user expectations for conversational AI services with consideration of user expertise. *Journal of Services Marketing*.

Schanke, S., Burtch, G., & Ray, G. (2021). Estimating the impact of "Humanizing" customer service chatbots. *Information Systems Research*, *32*(3), 736–751.

Pelau, C., Dabija, D., & Ene, I. (2021). What makes an AI device human-like? The role of interaction quality, empathy and perceived psychological anthropomorphic characteristics in the acceptance of artificial intelligence in the service industry. *Computers in Human Behavior*, *122*, 106855.

Wei, Y., Syahrivar, J., & Simay, A. E. (2024). Unveiling the influence of anthropomorphic chatbots on consumer behavioral intentions: evidence from China and Indonesia. *Journal of Research in Interactive Marketing*, *19*(1), 132–157.

Konya-Baumbach, E., Biller, M., & Von Janda, S. (2022). Someone out there? A study on the social presence of anthropomorphized chatbots. *Computers in Human Behavior*, *139*, 107513.

Kim, J., Giroux, M., & Lee, J. C. (2021). When do you trust AI? The effect of number presentation detail on consumer trust and acceptance of AI recommendations. *Psychology & Marketing*, *38*(7), 1140-1155.

Chinchanachokchai, S., Thontirawong, P., & Chinchanachokchai, P. (2021). A tale of two recommender systems: The moderating role of consumer expertise on artificial intelligence based product recommendations. *Journal of Retailing and Consumer Services*, *61*, 102528.

Xu, J., Tang, X., Lin, H., & Luo, Y. (2024). The impact of recommender type on tourist price sensitivity to travel plans. *Journal of Travel Research*, 00472875241261633.

Alexander, V., Blinder, C., & Zak, P. J. (2018). Why trust an algorithm? Performance, cognition, and neurophysiology. *Computers in Human Behavior*, *89*, 279-288.

Chen, S., Qiu, H., Zhao, S., Han, Y., He, W., Siponen, M., Mou, J., & Xiao, H. (2021). When more is less: The other side of artificial intelligence recommendation. *Journal of Management Science and Engineering*, *7*(2), 213–232.

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

Pizzi, G., Scarpi, D., & Pantano, E. (2020). Artificial intelligence and the new forms of interaction: Who has the control when interacting with a chatbot? *Journal of Business Research*, *129*, 878–890.

Chung, M., Ko, E., Joung, H., & Kim, S. J. (2018). Chatbot e-service and customer satisfaction regarding luxury brands. *Journal of Business Research*, *117*, 587–595.

Rhee, C. E., & Choi, J. (2020). Effects of personalization and social role in voice shopping: An experimental study on product recommendation by a conversational voice agent. *Computers in Human Behavior, 109*, 106359.

Rese, A., Ganster, L., & Baier, D. (2020). Chatbots in retailers' customer communication: How to measure their acceptance? *Journal of Retailing and Consumer Services, 56*, 102176.

Roy, R., & Naidoo, V. (2020). Enhancing chatbot effectiveness: The role of anthropomorphic conversational styles and time orientation. *Journal of Business Research*, *126*, 23–34.

Grewal, D., Satornino, C. B., Davenport, T., & Guha, A. (2024). How generative AI Is shaping the future of marketing. *Journal of the Academy of Marketing Science*, 1-21.

Brand, J., Israeli, A., & Ngwe, D. (2023). Using LLMs for market research. *Harvard Business School Marketing Unit Working Paper*, (23-062).

Castelo, N., Bos, M. W., & Lehmann, D. R. (2019). Task-Dependent algorithm aversion. *Journal of Marketing Research*, *56*(5), 809–825.

Arce-Urriza, M., Chocarro, R., Cortiñas, M., & Marcos-Matás, G. (2025). From familiarity to acceptance: The impact of Generative Artificial Intelligence on consumer adoption of retail chatbots. *Journal of Retailing and Consumer Services, 84*, 104234.

Osborne, M. R., & Bailey, E. R. (2025). Me vs. the machine? Subjective evaluations of human- and AI-generated advice. *Scientific Reports*, *15*(1).

Ali, F., Yasar, B., Ali, L., & Dogan, S. (2023). Antecedents and consequences of travelers' trust towards personalized travel recommendations offered by ChatGPT. *International Journal of Hospitality Management*, *114*, 103588.

Kim, J. H., Kim, J., Baek, T. H., & Kim, C. (2024a). ChatGPT personalized and humorous recommendations. *Annals of Tourism Research*, *110*, 103857.

Kim, J. H., Kim, J., Park, J., Kim, C., Jhang, J., & King, B. (2023c). When ChatGPT gives incorrect answers: The impact of inaccurate information by Generative AI on tourism Decision-Making. *Journal of Travel Research*.

Monteith, S., Glenn, T., Geddes, J. R., Whybrow, P. C., Achtyes, E., & Bauer, M. (2024). Artificial intelligence and increasing misinformation. *The British Journal of Psychiatry*, *224*(2), 33–35.

Baek, T. H., Kim, H. J., & Kim, J. (2025). AI-generated recommendations: Roles of language style, perceived AI human-likeness, and recommendation agent. *International Journal of Hospitality Management*, *126*, 104106.

Zhu, H., Zhu, Z., Ou, Y., & Yin, Y. (2023). To be precise (imprecise) in utilitarian (hedonic) contexts: Examining the influence of numerical precision on consumer reactions to artificial intelligence-based recommendations. *Psychology and Marketing*, *40*(12), 2668–2685.

Labrecque, L. I., Peña, P. Y., Leonard, H., & Leger, R. (2024). Not all sunshine and rainbows: exploring the dark side of AI in interactive marketing. *Journal of Research in Interactive Marketing*.

Chakraborty, D., Kar, A. K., Patre, S., & Gupta, S. (2024). Enhancing trust in online grocery shopping through generative AI chatbots. *Journal of Business Research*, *180*, 114737.

Iranmanesh, M., Senali, M. G., Ghobakhloo, M., Foroughi, B., Yadegaridehkordi, E., & Annamalai, N. (2024). Determinants of intention to use ChatGPT for obtaining shopping information. *The Journal of Marketing Theory and Practice*, 1–18.

Chang, W., & Park, J. (2024). A comparative study on the effect of ChatGPT recommendation and AI recommender systems on the formation of a consideration set. *Journal of Retailing and Consumer Services*, *78*, 103743.

Malikireddy, S. K. R. (2024). Revolutionizing Product Recommendations with Generative AI: Context-Aware Personalization at Scale.

Wang, W., Zhang, Y., & Chua, T. S. (2024). Recommendation in the Era of Generative Artificial Intelligence. In *Information Access in the Era of Generative AI* (pp. 201-221). Cham: Springer Nature Switzerland.

Adam, M., Wessel, M., & Benlian, A. (2020). AI-based chatbots in customer service and their effects on user compliance. *Electronic Markets, 31*(2), 427–445.

Klaus, P., & Zaichkowsky, J. L. (2021). The convenience of shopping via voice AI: Introducing AIDM. *Journal of Retailing and Consumer Services, 65*, 102490.

Balakrishnan, J., & Dwivedi, Y. K. (2021). Conversational commerce: entering the next stage of AI-powered digital assistants. *Annals of Operations Research*, *333*(2–3), 653–687.

Al-Hasan, T. M., Sayed, A. N., Bensaali, F., Himeur, Y., Varlamis, I., & Dimitrakopoulos, G. (2024). From traditional recommender systems to GPT-Based chatbots: a survey of recent developments and future directions. *Big Data and Cognitive Computing*, *8*(4), 36.

Ji, J., Li, Z., Xu, S., Hua, W., Ge, Y., Tan, J., & Zhang, Y. (2024, March). Genrec: Large language model for generative recommendation. In *European Conference on Information Retrieval* (pp. 494-502). Cham: Springer Nature Switzerland.

Lin, G., & Zhang, Y. (2023). Sparks of Artificial General Recommender (AGR): Experiments with ChatGPT. *Algorithms, 16*(9), 432.

Kumar, A., Shankar, A., Behl, A., Chakraborty, D., & Gundala, R. R. (2025). Anthropomorphic generative AI chatbots for enhancing customer engagement, experience and recommendation. *Journal of Consumer Marketing*. https://doi.org/10.1108/jcm-06-2024-6922

Luo, Y., Cheng, M., Zhang, H., Lu, J., & Chen, E. (2024). Unlocking the potential of large language models for explainable recommendations. In *Lecture notes in computer science* (pp. 286–303).

Abou-Shouk, M., Elbaz, A. M., Al-Leheabi, S. M. Z. M., AbuElEnain, E., & Shabana, M. M. (2024). Trusting ChatGPT usage in Personalized Travel Planning: The moderating role of privacy and Data Security. *Tourism and Hospitality Research*.

Balta, K. Y., Javidan, A. P., Walser, E., Arntfield, R., & Prager, R. (2025). Evaluating the appropriateness, consistency, and readability of ChatGPT in critical care recommendations. *Journal of Intensive Care Medicine*, *40*(2), 184-190.

Li, X., Grahl, J., & Hinz, O. (2021). How do recommender systems lead to consumer purchases? A causal mediation analysis of a field experiment. *Information Systems Research, 33*(2), 620–637.

Xiao, B., & Benbasat, I. (2007). E-commerce product recommendation agents: Use, characteristics, and impact. *MIS quarterly*, 137-209.

Go, E., & Sundar, S. S. (2019). Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions. *Computers in Human Behavior, 97*, 304–316.

Misischia, C. V., Poecze, F., & Strauss, C. (2022). Chatbots in customer service: Their relevance and impact on service quality. *Procedia Computer Science, 201*, 421–428.

Fleischner, M., & Grad, B. (2019). How chatbots will help transform your business. *American Marketing Association.*

Niu, B., & Mvondo, G. F. N. (2023). I Am ChatGPT, the ultimate AI Chatbot! Investigating the determinants of users' loyalty and ethical usage concerns of ChatGPT. *Journal of Retailing and Consumer Services*, *76*, 103562.

Ma, X., & Huo, Y. (2023). Are users willing to embrace ChatGPT? Exploring the factors on the acceptance of chatbots from the perspective of AIDUA framework. *Technology in Society*, *75*, 102362.

Paul, J., Ueno, A., & Dennis, C. (2023). ChatGPT and consumers: Benefits, Pitfalls and Future Research Agenda. *International Journal of Consumer Studies*, *47*(4), 1213–1225.

Chong, T., Yu, T., Keeling, D. I., & De Ruyter, K. (2021). AI-chatbots on the services frontline addressing the challenges and opportunities of agency. *Journal of Retailing and Consumer Services*, *63*, 102735.

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management*, *49*, 157–169.

Hsu, C., & Lin, J. C. (2022). Understanding the user satisfaction and loyalty of customer service chatbots. *Journal of Retailing and Consumer Services*, *71*, 103211.

Zhu, Y., Zhang, J., Wu, J., & Liu, Y. (2022). AI is better when I'm sure: The influence of certainty of needs on consumers' acceptance of AI chatbots. *Journal of Business Research*, *150*, 642–652.

Romero-Charneco, M., Casado-Molina, A., Alarcón-Urbistondo, P., & Sánchez, J. P. C. (2024). Customer intentions toward the adoption of WhatsApp chatbots for restaurant recommendations. *Journal of Hospitality and Tourism Technology*.

Rebitschek, F. G. (2024). Boosting consumers: Algorithm-supported decision-making under uncertainty to (learn to) navigate algorithm-based decision environments. In: Knowledge and digital technology. Cham: Springer Nature Switzerland. pp. 63-77.

Wong, I. A., Lian, Q. L., & Sun, D. (2023). Autonomous travel decision-making: An early glimpse into ChatGPT and generative AI. *Journal of Hospitality and Tourism Management*, *56*, 253–263.

Chen, J., Le, T., & Florence, D. (2021). Usability and responsiveness of artificial intelligence chatbot on online customer experience in e-retailing. *International Journal of Retail & Distribution Management*, *49*(11), 1512–1531.

Brill, T. M., Munoz, L., & Miller, R. J. (2022). Siri, Alexa, and other digital assistants: a study of customer satisfaction with artificial intelligence applications. In *The role of smart technologies in decision making* (pp. 35-70). Routledge.

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., ... & Wright, R. (2023). Opinion Paper:"So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International journal of information management*, *71*, 102642.

Fernandes, T., & Oliveira, E. (2020). Understanding consumers' acceptance of automated technologies in service encounters: Drivers of digital voice assistants adoption. *Journal of Business Research*, *122*, 180–191.

Hsu, P. F., Nguyen, T., Wang, C. Y., & Huang, P. J. (2023). Chatbot commerce—How contextual factors affect Chatbot effectiveness. *Electronic Markets*, *33*(1), 14.

Inavolu, S. M. (2024). Exploring AI-Driven customer service: evolution, architectures, opportunities, challenges and future directions. *International Journal for Multidisciplinary Research*, *6*(3).

Jiménez-Barreto, J., Rubio, N., & Molinillo, S. (2023). How chatbot language shapes consumer perceptions: The role of concreteness and shared competence. *Journal of Interactive Marketing*, *58*(4), 380-399.

Kasilingam, D. L. (2020). Understanding the attitude and intention to use smartphone chatbots for shopping. *Technology in Society*, *62*, 101280.

Kim, S. Y., Schmitt, B. H., & Thalmann, N. M. (2019). Eliza in the uncanny valley: Anthropomorphizing consumer robots increases their perceived warmth but decreases liking. *Marketing letters*, *30*, 1-12.

Komiak, N., & Benbasat, N. (2006). The effects of personalization and familiarity on trust and adoption of recommendation agents. *MIS Quarterly*, *30*(4), 941.

Leung, C. H., & Chan, W. T. Y. (2020). Retail chatbots: The challenges and opportunities of conversational commerce. *Journal of Digital & Social Media Marketing.*, *8*(1), 68.

Li, B., Chen, Y., Liu, L., & Zheng, B. (2023). Users' intention to adopt artificial intelligence-based chatbot: a meta-analysis. *Service Industries Journal*, *43*(15–16), 1117–1139.

McKinsey, 2024. The state of AI in early 2024 | McKinsey. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai

Nordheim, C. B., Følstad, A., & Bjørkli, C. A. (2019). An Initial Model of Trust in Chatbots for Customer Service—Findings from a Questionnaire Study. *Interacting With Computers*, *31*(3), 317–335.

Ooi, K., Tan, G. W., Al-Emran, M., Al-Sharafi, M. A., Capatina, A., Chakraborty, A., Dwivedi, Y. K., Huang, T., Kar, A. K., Lee, V., Loh, X., Micu, A., Mikalef, P., Mogaji, E., Pandey, N., Raman, R., Rana, N. P., Sarker, P., Sharma, A., . . . Wong, L. (2023). The potential of generative artificial intelligence across disciplines: perspectives and future directions. *Journal of Computer Information Systems*, 1–32.

Pathak, K., Prakash, G., Samadhiya, A., Kumar, A., & Luthra, S. (2024). Impact of Gen-AI chatbots on consumer services experiences and behaviors: Focusing on the sensation of awe and usage intentions through a cybernetic lens. *Journal of Retailing and Consumer Services*, *82*, 104120.

Przegalinska, A., Ciechanowski, L., Stroz, A., Gloor, P., & Mazurek, G. (2019). In bot we trust: A new methodology of chatbot performance measures. *Business Horizons*, *62*(6), 785–797.

Rapp, A., Curti, L., & Boldi, A. (2021). The human side of human-chatbot interaction: A systematic literature review of ten years of research on text-based chatbots. *International Journal of Human-Computer Studies*, *151*, 102630.

Shahzad, M. F., Xu, S., An, X., & Javed, I. (2024). Assessing the impact of AI-chatbot service quality on user e-brand loyalty through chatbot user trust, experience and electronic word of mouth. *Journal of Retailing and Consumer Services*, *79*, 103867.

Silva, S. C., De Cicco, R., Vlačić, B., & Elmashhara, M. G. (2022). Using chatbots in e-retailing – how to mitigate perceived risk and enhance the flow experience. *International Journal of Retail & Distribution Management*, *51*(3), 285–305.

Shawar, B. A., & Atwell, E. (2007). Chatbots: Are they Really Useful? *Deleted Journal*, *22*(1), 29–49.

Jin, M., Yang, Z., Freling, T. L., & Janakiraman, N. (2025). The Human Superiority Effect in Advice Taking: A Multimethod Exploration and Implications for Policy Makers and Governmental Organizations. *JOURNAL OF PUBLIC POLICY & MARKETING*.

Bonezzi, A., Ostinelli, M., & Melzner, J. (2022). The human black-box: The illusion of understanding human better than algorithmic decision-making. *Journal of Experimental Psychology General*, *151*(9), 2250–2258.

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, *151*, 90-103.

Ruan, Y., & Mezei, J. (2022). When do AI chatbots lead to higher customer satisfaction than human frontline employees in online shopping assistance? Considering product attribute type. *Journal of Retailing and Consumer Services*, *68*, 103059.

Wien, A. H., & Peluso, A. M. (2021). Influence of human versus AI recommenders: The roles of product type and cognitive processes. *Journal of Business Research*, *137*, 13–27.

Wen, Y., & Laporte, S. (2024). Experiential narratives in marketing: A comparison of generative AI and human content. *Journal of Public Policy & Marketing*, 07439156241297973.

Davenport, T. H., Lucker, J., Deloitte Review, Lopez, J., Sarni, W., Conroy, P., Narula, A., Finn, J., Del, V., Raynor, M. E., Ahmed, M., Guszcza, J., Eggers, W. D., Macmillan, P., Giffi, C., Dollar, B., Gangula, B., Rodriguez, M. D., Schatsky, D., . . . Moffatt, J. (n.d.). Deloitte Review. *Deloitte*. https://www2.deloitte.com/content/dam/insights/us/collections/Issue-16-MASTER.pdf

https://www.seozoom.it/customer-journey/

Park, D., Lee, J., & Han, I. (2007). The effect of On-Line consumer reviews on consumer purchasing intention: the moderating role of involvement. *International Journal of Electronic Commerce*, *11*(4), 125–148.

Filieri, R., McLeay, F., Tsui, B., & Lin, Z. (2018). Consumer perceptions of information helpfulness and determinants of purchase intention in online consumer reviews of services. *Information & Management*, *55*(8), 956–970.

Granovetter, M. S. (1973). The strength of weak ties. *American Journal of Sociology*, *78*(6), 1360–1380.

Bataineh, A. Q. (2015). The impact of perceived e-WOM on purchase intention: The mediating role of corporate image. *International Journal of Marketing Studies*, *7*(1).

Nuseir, M. T. (2019). The impact of electronic word of mouth (e-WOM) on the online purchase intention of consumers in the Islamic countries – a case of (UAE). *Journal of Islamic Marketing*, *10*(3), 759–767.

Almana, A. M., & Mirza, A. A. (2013). The impact of electronic word of mouth on consumers' purchasing decisions. *International Journal of Computer Applications*, *82*(9), 23-31.

Jalilvand, M. R., & Samiei, N. (2012). The effect of electronic word of mouth on brand image and purchase intention. *Marketing Intelligence & Planning*, *30*(4), 460–476.

Yaylc, A., & Bayram, M. (2012). e-WOM: the effects of online consumer reviews on purchasing decisions. *International Journal of Internet Marketing and Advertising*, *7*(1), 51.

Yoon, S. J. (2012). A social network approach to the influences of shopping experiences on e-wom. *Journal of Electronic Commerce Research*, *13*(3), 213.

Christodoulides, G., Michaelidou, N., & Argyriou, E. (2012). Cross-national differences in e-WOM influence. *European Journal of Marketing*, *46*(11/12), 1689–1707.

Poturak, M., & Softić, S. (2019). Influence of social media content on consumer purchase intention: Mediation effect of Brand equity. *Eurasian Journal of Business and Economics*, *12*(23), 17–43.

Kudeshia, C., & Kumar, A. (2017). Social eWOM: does it affect the brand attitude and purchase intention of brands? *Management Research Review*, *40*(3), 310–330.

Ventre, I., & Kolbe, D. (2020). The impact of perceived usefulness of online reviews, trust and perceived risk on online purchase intention in emerging markets: A Mexican perspective. *Journal of International Consumer Marketing*, *32*(4), 287–299.

Zhu, L., Li, H., Wang, F., He, W., & Tian, Z. (2020). How online reviews affect purchase intention: a new model based on the stimulus-organism-response (S-O-R) framework. *Aslib Journal of Information Management*, *72*(4), 463–488.

Chakraborty, U. (2019). The impact of source credible online reviews on purchase intention: The mediating roles of brand equity dimensions. *Journal of Research in Interactive Marketing*, *13*(2), 142-161.

Aaker, D.A. (1991), Managing Brand Equity, Free Press, New York, NY

Jiménez, F. R., & Mendoza, N. A. (2013). Too popular to ignore: the influence of online reviews on purchase intentions of search and experience products. *Journal of Interactive Marketing*, *27*(3), 226–235.

Furner, C. P., & Zinko, R. A. (2016). The influence of information overload on the development of trust and purchase intention based on online product reviews in a mobile vs. web environment: an empirical investigation. *Electronic Markets*, *27*(3), 211–224.

Chen, C., & Chang, Y. (2018). What drives purchase intention on Airbnb? Perspectives of consumer reviews, information quality, and media richness. *Telematics and Informatics*, *35*(5), 1512–1523.

Chen, T., Samaranayake, P., Cen, X., Qi, M., & Lan, Y. (2022). The impact of online reviews on consumers' purchasing decisions: evidence from an Eye-Tracking study. *Frontiers in Psychology*, *13*.

Mauri, A. G., & Minazzi, R. (2013). Web reviews influence on expectations and purchasing intentions of hotel potential customers. *International Journal of Hospitality Management*, *34*, 99–107.

Reimer, T., & Benkenstein, M. (2016). When good WOM hurts and bad WOM gains: The effect of untrustworthy online reviews. *Journal of Business Research*, *69*(12), 5993–6001.

Onofrei, G., Filieri, R., & Kennedy, L. (2021). Social media interactions, purchase intention, and behavioural engagement: The mediating role of source and content factors. *Journal of Business Research*, *142*, 100–112.

Peña-García, N., Gil-Saura, I., Rodríguez-Orejuela, A., & Siqueira-Junior, J. R. (2020). Purchase intention and purchase behavior online: A cross-cultural approach. *Heliyon*, *6*(6), e04284.

Chakraborty, U., & Bhat, S. (2017). The effects of credible online reviews on brand equity dimensions and its consequence on consumer behavior. *Journal of Promotion Management*, *24*(1), 57–82.

Xiao, L., Guo, F., Yu, F., & Liu, S. (2019). The effects of online shopping context cues on consumers' purchase intention for Cross-Border E-Commerce sustainability. *Sustainability*, *11*(10), 2777.

Fan, Y. W., & Miao, Y. F. (2012). Effect of electronic word-of-mouth on consumer purchase intention: The perspective of gender differences. *International Journal of electronic business management*, *10*(3), 175.

Hajli, N., Sims, J., Zadeh, A. H., & Richard, M. (2016). A social commerce investigation of the role of trust in a social networking site on purchase intentions. *Journal of Business Research*, *71*, 133–141.

Wang, J., & Chang, C. (2013). How online social ties and product-related risks influence purchase intentions: A Facebook experiment. *Electronic Commerce Research and Applications*, *12*(5), 337–346.

Prasad, S., Garg, A., & Prasad, S. (2019). Purchase decision of generation Y in an online environment. *Marketing Intelligence & Planning*, *37*(4), 372–385.

Di Pietro, L., & Pantano, E. (2012). An empirical investigation of social network influence on consumer purchasing decision: The case of Facebook. *Journal of Direct Data and Digital Marketing Practice*, *14*(1), 18–29.

Bae, S., & Lee, T. (2010). Gender differences in consumers' perception of online consumer reviews. *Electronic Commerce Research*, *11*(2), 201–214.

Huang, J., Guo, Y., Wang, C., & Yan, L. (2019). You touched it and I'm relieved! The effect of online review's tactile cues on consumer's purchase intention. *Journal of Contemporary Marketing Science*, *2*(2), 155–175.

Hussain, S., Ahmed, W., Jafar, R. M. S., Rabnawaz, A., & Jianzhou, Y. (2017). eWOM source credibility, perceived risk and food product customer's information adoption. *Computers in Human Behavior, 66,* 96–102.

Van Slyke, C., Comunale, C. L., & Belanger, F. (2002). Gender differences in perceptions of web-based shopping. *Communications of the ACM*, *45*(8), 82–86.

Huang, J., & Chen, Y. (2006). Herding in online product choice. *Psychology and Marketing*, *23*(5), 413–428.

Cheong, H. J., & Morrison, M. A. (2008). Consumers' reliance on product information and recommendations found in UGC. *Journal of Interactive Advertising*, *8*(2), 38–49.

Kim, M. J., Kang, S., Hall, C. M., Kim, J. S., & Promsivapallop, P. (2024b). Unveiling the impact of ChatGPT on travel consumer behaviour: exploring trust, attribute, and sustainable-tourism action. *Current Issues in Tourism*, 1–6.

Choi, M., Choi, Y., Bangura, E., & Kim, D. (2024). ChatGPT or online review: Which is a better determinant of customers' trust in Airbnb listings and stay intention? *International Journal of Hospitality Management*, *122*, 103852.

Foroughi, B., Iranmanesh, M., Yadegaridehkordi, E., Wen, J., Ghobakhloo, M., Senali, M. G., & Annamalai, N. (2024). Factors affecting the use of ChatGPT for obtaining shopping information. *International Journal of Consumer Studies*, *49*(1).

Abou-Shouk, M., Abdelhakim, A. S., Elgarhy, S. D., Rabea, A., & Abdulmawla, M. (2025). ChatGPT usage intention for tourism and hospitality customers. *Tourism Recreation Research*, 1–18.

Xu, H., Law, R., Lovett, J., Luo, J. M., & Liu, L. (2024). Tourist acceptance of ChatGPT in travel services: the mediating role of parasocial interaction. *Journal of Travel & Tourism Marketing*, *41*(7), 955–972.

Solomovich, L., & Abraham, V. (2024). Exploring the influence of ChatGPT on tourism behavior using the technology acceptance model. *Tourism Review.*

Kim, J. H., Kim, J., Kim, S., & Hailu, T. B. (2023d). Effects of AI ChatGPT on travelers' travel decision-making. *Tourism Review*, *79*(5), 1038–1057.

Shin, S., Kim, J., Lee, E., Yhee, Y., & Koo, C. (2025). ChatGPT for trip planning: The effect of narrowing down options. *Journal of Travel Research*, *64*(2), 247-266.

Alizadeh, H., & Nazarpour Kashani, H. (2025). The impact of perceived experience with ChatGPT on online consumers' information searching behavior: an empirical study of Iranian college students. *Asia Pacific Journal of Marketing and Logistics*, *37*(4), 1007-1028.

Yang, S., Xie, W., Chen, Y., Li, Y., Jiang, H., & zhou, W. (2024). Warmth or competence? Understanding voice shopping intentions from human-AI interaction perspective. *Electronic Commerce Research*, 1-30.

Sidlauskiene, J., Joye, Y., & Auruskeviciene, V. (2023). AI-based chatbots in conversational commerce and their effects on product and price perceptions. *Electronic Markets*, *33*(1), 24.

Kim, M., & Koo, C. (2024). A study of the behavioral intention on Conversational ChatGPT for Tourism Information Search Service: Focusing on the role of Cognitive and affective trust. *Information Systems Review*, *26*(1), 119–149.

Ayemowa, M. O., Ibrahim, R., & Khan, M. M. (2024). Analysis of Recommender System Using Generative Artificial Intelligence: A Systematic Literature review. *IEEE Access*, *12*, 87742–87766.

Mukande, T., Ali, E., Caputo, A., Dong, R., & O'Connor, N. E. (2024). MMCREC: Towards Multi-modal Generative AI in conversational recommendation. In *Lecture notes in computer science* (pp. 316–325).

Aggarwal, N. A. (2025). Evolution of recommendation systems in the age of Generative AI. *International Journal of Science and Research Archive*, *14*(1), 485–492.

Deldjoo, Y., He, Z., McAuley, J., Korikov, A., Sanner, S., Ramisa, A., Vidal, R., Sathiamoorthy, M., Kasirzadeh, A., & Milano, S. (2025). Tutorial on Recommendation with Generative Models (Gen-RecSys). *Proceedings of the Eighteenth ACM International Conference on Web Search and Data Mining*, 1002–1004.

Kim, J. H., Kim, J., Kim, C., & Kim, S. (2023b). Do you trust ChatGPTs? Effects of the ethical and quality issues of generative AI on travel decisions. *Journal of Travel & Tourism Marketing*, *40*(9), 779–801.

Pham, H. C., Duong, C. D., & Nguyen, G. K. H. (2024). What drives tourists' continuance intention to use ChatGPT for travel services? A stimulus-organism-response perspective. *Journal of Retailing and Consumer Services*, *78*, 103758.

Park, C., & Jun, J. K. (2003). A cross-cultural comparison of Internet buying behavior: Effects of Internet usage, perceived risks, and innovativeness. *International Marketing Review*, *20*(5), 534-553.

Bhatnagar, A., Misra, S., & Rao, H. R. (2000). On risk, convenience, and Internet shopping behavior. *Communications of the ACM*, *43*(11), 98-105.

Paluch, S., & Wünderlich, N. V. (2016). Contrasting risk perceptions of technology-based service innovations in inter-organizational settings. *Journal of business Research*, *69*(7), 2424-2431.

Ariffin, S. K., Mohan, T., & Goh, Y. (2018). Influence of consumers' perceived risk on consumers' online purchase intention. *Journal of Research in Interactive Marketing*, *12*(3), 309–327.

Zhong-Gang, Y., Xiao-Ya, W., & Economics, S. O. J. S. E. (2015). Research progress and future prospect on online reviews and consumer behavior. *Soft Science*, *6*, 20.

Miyazaki, A. D., & Fernandez, A. (2001). Consumer perceptions of privacy and security risks for online shopping. *Journal of Consumer Affairs*, *35*(1), 27–44.

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: a perceived risk facets perspective. *International journal of human-computer studies*, *59*(4), 451-474.

Bahtar, A. Z., & Muda, M. (2016). The Impact of User – Generated Content (UGC) on Product Reviews towards Online Purchasing – A Conceptual Framework. *Procedia Economics and Finance*, *37*, 337–342.

Silalahi, A. D. K. (2024). Can Generative Artificial Intelligence Drive Sustainable Behavior? A Consumer Adoption Model for AI-Driven Recommendations. *SSRN Electronic Journal*.

Peterson, R. A., & Merino, M. C. (2003). Consumer information search behavior and the Internet. *Psychology & Marketing*, *20*(2), 99-121.

Sheehan, K. B. (1999). An investigation of gender differences in on-line privacy concerns and resultant behaviors. *Journal of interactive marketing*, *13*(4), 24-38.

Hong, I. B., & Cha, H. S. (2013). The mediating role of consumer trust in an online merchant in predicting purchase intention. *International Journal of Information Management*, *33*(6), 927-939.

Bai, Y., Yao, Z., & Dou, Y. F. (2015). Effect of social commerce factors on user purchase behavior: An empirical investigation from renren. com. *International Journal of Information Management*, *35*(5), 538-550.

Pelaez, A., Chen, C. W., & Chen, Y. X. (2019). Effects of perceived risk on intention to purchase: A meta-analysis. *Journal of computer information systems*, *59*(1), 73-84.

Park, S., & Tussyadiah, I. P. (2017). Multidimensional facets of perceived risk in mobile travel booking. *Journal of Travel Research*, *56*(7), 854-867.

Farivar, S., Turel, O., & Yuan, Y. (2017). A trust-risk perspective on social commerce use: an examination of the biasing role of habit. *Internet Research*, *27*(3), 586-607.

Chiu, C. M., Wang, E. T., Fang, Y. H., & Huang, H. Y. (2014). Understanding customers' repeat purchase intentions in B2C e-commerce: the roles of utilitarian value, hedonic value and perceived risk. *Information systems journal*, *24*(1), 85-114.

Singh, S., & Srivastava, S. (2018). Moderating effect of product type on online shopping behaviour and purchase intention: An Indian perspective. *Cogent Arts & Humanities*, *5*(1), 1495043.

Dai, B., Forsythe, S. and Kwon, W.S. (2014). The impact of online shopping experience on risk perceptions and online purchase intentions: does product category matter. *Journal of Electronic Commerce Research, 15*(1), 13-24.

Dowling, G. R., & Staelin, R. (1994). A model of perceived risk and intended risk-handling activity. *Journal of Consumer Research*, *21*(1), 119-134.

Lee, K. S., & Tan, S. J. (2003). E-retailing versus physical retailing: A theoretical model and empirical test of consumer choice. *Journal of business research*, *56*(11), 877-885.

Laroche, M., Yang, Z., McDougall, G. H., & Bergeron, J. (2005). Internet versus bricks-and-mortar retailers: An investigation into intangibility and its consequences. *Journal of Retailing*, *81*(4), 251-267.

Ariff, M. S. M., Sylvester, M., Zakuan, N., Ismail, K., & Ali, K. M. (2014, June). Consumer perceived risk, attitude and online shopping behaviour; empirical evidence from Malaysia. In *IOP Conference Series: Materials Science and Engineering* (Vol. 58, No. 1, p. 012007). IOP Publishing.

Almousa, M. (2011). Perceived Risk in Apparel Online Shopping: A Multi Dimensional Perspective/Le Risque Perçu Dans Des Achats En Ligne D'habillement: Une Perspective De Dimensionnelle Multiple. *Canadian Social Science*, *7*(2), 23.

Liebermann, Y., & Stashevsky, S. (2002). Perceived risks as barriers to Internet and e-commerce usage. *Qualitative Market Research: An International Journal*, *5*(4), 291-300.

Zheng, L., Favier, M., Huang, P., & Coat, F. (2012). Chinese consumer perceived risk and risk relievers in e-shopping for clothing. *Journal of Electronic Commerce Research*, *13*(3), 255.

Liu, X., & Wei, K. K. (2003). An empirical study of product differences in consumers' E-commerce adoption behavior. *Electronic Commerce Research and Applications*, *2*(3), 229-239.

Kim, J., & Lennon, S. J. (2013). Effects of reputation and website quality on online consumers' emotion, perceived risk and purchase intention: Based on the stimulus-organism-response model. *Journal of Research in Interactive Marketing*, *7*(1), 33-56.

Akhlaq, A., & Ahmed, E. (2015). Digital commerce in emerging economies: Factors associated with online shopping intentions in Pakistan. *International Journal of Emerging Markets*, *10*(4), 634-647.

Godes, D., & Mayzlin, D. (2004). Using online conversations to study Word-of-Mouth communication. *Marketing Science*, *23*(4), 545–560

Zhao, X., Deng, S., & Zhou, Y. (2017). The impact of reference effects on online purchase intention of agricultural products: The moderating role of consumers' food safety consciousness. *Internet Research*, *27*(2), 233-255.

Mitchell, V. (1999). Consumer perceived risk: conceptualisations and models. *European Journal of Marketing*, *33*(1/2), 163–195.

Bhukya, R., & Singh, S. (2015). The effect of perceived risk dimensions on purchase intention: An empirical evidence from Indian private labels market. *American Journal of Business*, *30*(4), 218-230.

Han, M. C., & Kim, Y. (2017). Why consumers hesitate to shop online: Perceived risk and product involvement on Taobao. com. *Journal of Promotion Management*, *23*(1), 24-44.

Tsai, Y. C., & Yeh, J. C. (2010). Perceived risk of information security and privacy in online shopping: A study of environmentally sustainable products. *African Journal of Business Management*, *4*(18), 4057.

Forsythe, S. M., & Shi, B. (2003). Consumer patronage and risk perceptions in Internet shopping. *Journal of Business Research*, *56*(11), 867-875.

Shang, Q., Pei, G., & Jin, J. (2017). My friends have a word for it: event-related potentials evidence of how social risk inhibits purchase intention. *Neuroscience Letters*, *643*, 70-75.

Jacoby, J. and Kaplan, L. (1972). The components of perceived risk. *Advances in Consumer Research, 59(*3), 287-291.

Masoud, E. Y. (2013). The effect of perceived risk on online shopping in Jordan. *European Journal of Business and Management*, *5*(6), 76-87.

Pavlou, P. A. (2003). Consumer acceptance of electronic commerce: Integrating trust and risk with the technology acceptance model. *International Journal of Electronic Commerce, 7*(3), 101–134.

Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. *Decision Support Systems*, *44*(2), 544-564.

Lee, M. K., & Turban, E. (2001). A trust model for consumer internet shopping. *International Journal of Electronic Commerce*, *6*(1), 75-91.

O’cass, A., & Fenech, T. (2003). Web retailing adoption: exploring the nature of internet users Web retailing behaviour. *Journal of Retailing and Consumer services*, *10*(2), 81-94.

Van der Heijden, H., Verhagen, T., Creemers, M. (2003). Understanding online purchase intentions: Contributions from technology and trust perspectives. *European Journal of Information Systems, 12*(1), 41-48.

Gibreel, O., AlOtaibi, D. A., & Altmann, J. (2018). Social commerce development in emerging markets. *Electronic Commerce Research and Applications*, *27,* 152-162.

Han, B. O., & Windsor, J. (2011). User's willingness to pay on social network sites. *Journal of Computer Information Systems*, *51*(4), 31-40.

Zahid, M. M., Ali, B., Ahmad, M. S., Thurasamy, R., & Amin, N. (2018). Factors affecting purchase intention and social media publicity of green products: The mediating role of concern for consequences. *Corporate Social Responsibility and Environmental Management*, *25*(3), 225-236.

Huifeng, P., & Ha, H. (2021). Temporal effects of online customer reviews on restaurant visit intention: the role of perceived risk. *Journal of Hospitality Marketing & Management*, *30*(7), 825–844.

Yadav, N., Verma, S., & Chikhalkar, R. (2023). Online reviews towards reducing risk. *Journal of Tourism Futures*, *10*(2), 299–316.

Huifeng, P., Ha, H., & Lee, J. (2020). Perceived risks and restaurant visit intentions in China: Do online customer reviews matter? *Journal of Hospitality and Tourism Management*, *43*, 179–189.

Gavilan, D., Fernández-Lores, S., & Martinez-Navarro, G. (2019). The influence of Online Ratings on Film Choice: Decision Making and Perceived Risk. *Communication & Society*, *32*(2), 45–59.

Hwang, J., & Han, E. (2023). Is no feedback perceived as a risk in online reviews? *Journal of Consumer Behaviour*, *22*(5), 1211–1223.

Roy, R., & Shaikh, A. (2024). The impact of online consumer review confusion on online shopping cart abandonment: A mediating role of perceived risk and moderating role of mindfulness. *Journal of Retailing and Consumer Services*, *81*, 103941.

Lam, T., Heales, J., & Hartley, N. (2025). The role of positive online reviews in risk-based consumer behaviours: an information processing perspective. *Aslib Journal of Information Management*, *77*(2), 282-305.

Helfiyana, H., Alwie, A. F., & Samsir, S. (2024). The Influence of Online Customer Review and Perceived Risk on E-Trust and Purchase Intention on E-Commerce Lazada in Pekanbaru City. *InJEBA: International Journal of Economics, Business and Accounting*, *2*(3), 295-310.

Chang, C. C., & Chin, Y. C. (2010). The impact of recommendation sources on online purchase intentions: The moderating effects of gender and perceived risk. *World Academy of Science, Engineering and Technology*, *66*(6), 111-114.

Sembiring, T. H., & Nisa, P. C. (2023). Perceived Value of Online Reviews, Trust, Risk Perception, Purchase Intention and Actual Purchase.

Islam, M. T., Pandey, U., & Kumar, J. (2024). Electronic word-of-mouth and Indian solo female travellers' hotel booking intention: Moderating role of perceived risk. *International Social Science Journal*, *74*(254), 1593-1609.

Cuong, D. T. (2024). Examining How Electronic Word-of-Mouth Information Influences Customers' Purchase Intention: The Moderating Effect of Perceived Risk on E-Commerce Platforms. *SAGE Open*, *14*(4), 21582440241309408.

Mladenović, D., Beheshti, M., Kolar, T., Ismagilova, E., & Dwivedi, Y. K. (2024). Synthetic WOM? The Emergence of Generative Artificial Intelligence-Induced Recommendations. *Journal of Computer Information Systems*, 1-18.

Christensen, J., Hansen, J. M., & Wilson, P. (2025). Understanding the role and impact of Generative Artificial Intelligence (AI) hallucination within consumers' tourism decision-making processes. *Current Issues in Tourism*, *28*(4), 545-560.

Huang, G. I., Wong, I. A., Zhang, C. J., & Liang, Q. (2025). Generative AI inspiration and hotel recommendation acceptance: Does anxiety over lack of transparency matter? *International Journal of Hospitality Management*, *126*, 104112.

Zhou, T., & Wu, X. (2024). Examining generative AI user disclosure intention: An ELM perspective. *Universal Access in the Information Society*, 1-12.

Alamri, J. M. (2025). Antecedents of Generative Artificial Intelligence Technology Adoption: Extended Innovation of Diffusion Model with Cultural Dimensions and Risks Perceptions. *Journal of Ecohumanism*, *4*(1), 1718-1738.

Ongfeng Hu, Jiang, H., Gong, C., First, & Hu, Y. (2024). Analysis of Key Factors in Corporate Adoption of Generative Artificial Intelligence Based on the UTAUT2 Model. *Journal of the Korea Society of Computer and Information*, *29*(7), 53–71.

Seyfi, S., Kim, M. J., Nazifi, A., Murdy, S., & Vo-Thanh, T. (2025). Understanding tourist barriers and personality influences in embracing generative AI for travel planning and decision-making. *International Journal of Hospitality Management*, *126*, 104105.

Murshidi, G. A., Shulgina, G., Kapuza, A., & Costley, J. (2024). How understanding the limitations and risks of using ChatGPT can contribute to willingness to use. *Smart Learning Environments*, *11*(1).

Han, H., Kim, S., Hailu, T. B., Al-Ansi, A., Loureiro, S. M. C., & Kim, J. J. (2025). Determinants of approach behavior for ChatGPT and their configurational influence in the hospitality and tourism sector: a cumulative prospect theory. *International Journal of Contemporary Hospitality Management*, *37*(1), 113-139.

Sallam, M., Elsayed, W., Al-Shorbagy, M., Barakat, M., El Khatib, S., Ghach, W., ... & Malaeb, D. (2024, August). ChatGPT usage and attitudes are driven by perceptions of usefulness, ease of use, risks, and psycho-social impact: a study among university students in the UAE. In *Frontiers in Education* (Vol. 9, p. 1414758). Frontiers Media SA.

YILMAZEL, A. P. S. E. THE EFFECT OF PERCEIVED RISKS IN CONTENT PRODUCTION WITH ARTIFICIAL INTELLIGENCE ON CONSUMERS'ATTITUDES AND BEHAVIORAL INTENTIONS.

Remountakis, M., Kotis, K., Kourtzis, B., & Tsekouras, G. E. (2023). Using ChatGPT and persuasive technology for personalized recommendation messages in hotel upselling. *Information*, *14*(9), 504.

Duwadi, S., & Cautinho, C. (2024). ChatGPT based recommendation system for retail shops. *Procedia Computer Science*, *237*, 253–260.

Park, D. H., & Lee, J. (2008). eWOM overload and its effect on consumer behavioral intention depending on consumer involvement. *Electronic Commerce Research and Applications*, *7*(4), 386-398.

Hayes, A. F. (2017). Introduction to mediation, moderation, and conditional process analysis: A regression-based approach. New York: Guilford Press.

Spears, N., & Singh, S. N. (2004). Measuring attitude toward the brand and purchase intentions. *Journal of Current Issues & Research in Advertising*, *26*(2), 53-66.

Dodds, W. B., Monroe, K. B., & Grewal, D. (1991). Effects of price, brand, and store information on buyers' product evaluations. *Journal of Marketing Research*, *28*(3), 307.

Cox, A. D., Cox, D., & Zimet, G. (2006). Understanding consumer responses to product risk information. *Journal of Marketing*, *70*(1), 79-91.