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The impact of conversational AI on memory retention: a study of digital amnesia in the context of product research with ChatGPT

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The impact of conversational AI on memory retention :

A study of Digital Amnesia in the context of Product Research with ChatGPT

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Elsa Lebleu

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LIST OF ABBREVIATIONS

AI	Artificial Intelligence
B2C	Business-to-Consumer
CFA	Confirmatory Factor Analysis
CFI	Comparative Fit Index
GDPR	General Data Protection Regulation
GPT	Generative Pre-trained Transformer
NLP	Natural Language Processing
RMSEA	Root Mean Square Error of Approximation
SEA	Search Engine Advertising
SEO	Search Engine Optimization
SEM	Structural Equation Modeling
TAM	Technology Acceptance Model
UTAUT	Unified Theory of Acceptance and Use of Technology

ABSTRACT

In a context of information overload and the rise of AI-powered conversational agents, this research explores the impact of using ChatGPT on consumers' non-assisted memory when searching for product-related information. Through an exploratory quantitative study including an experimental component, this work examines whether a high reliance on these tools, combined with a high level of trust, can lead to cognitive offloading that affects information retention. The theoretical model integrates trust as a mediating variable, as well as information complexity, age, and education level as moderators. Although no hypothesis has been formally validated, the results nevertheless provide valuable insights for both academic research and marketing strategies, highlighting a possible paradox between technological efficiency and cognitive engagement.

Keywords: Artificial Intelligence, Conversational AI, ChatGPT, non-assisted memory, cognitive offloading, digital amnesia, exploratory quantitative study, memory retention

I. Introduction

1.1. Context

In the digital era, individuals are continuously being bombarded with more information than ever. Every day, without necessarily realizing it, we are exposed to a huge stream of data online, where we usually spend a lot of our time, which can sometimes feel overwhelming. This overload of information makes it harder to focus, process and retain important information. The vast amount of content available on websites and across social media feeds creates a busy mind, maybe even in overdrive, also affecting how well we remember information.

This situation is intensified by the intentional design of digital platforms, which aimed at capturing and retaining users' attention through mechanisms such as notifications, alerts, personalized content and gamification elements, making attention increasingly elusive (Dabbish et al., 2011). As Lin et al. (2015) pointed out, the continuous flow of digital solicitations can overload the brain, weakening its ability to process and store information in the long-term. This phenomenon is part of a broader trend that Firth et al. (2019) describe as a transition from the information age to the interruption age, characterized by continuous partial attention: a state in which attention is constantly divided among multiple tasks or stimuli, without deep engagement in any of them.

In this context of constant cognitive solicitation, Artificial Intelligence (AI) plays an increasingly central role in how individuals access information. The introduction of AI tools into daily and professional activities represents a major shift, with the potential to revolutionize interactions between businesses and their customers (McLean & Osei-Frimpong, 2019). Artificial Intelligence has gained economic and social relevance with advances in machine learning and big data, transforming industry structures, processes, and practices (Przegalinska et al., 2019; Buhalis et al., 2019). Among these tools, intelligent conversational agents (ICAs) such as ChatGPT, Bard, Bing Chat, and Perplexity AI offer users unprecedented capabilities, ranging from solving complex problems to instant access to vast amounts of data, as well as generating creative content (Dergaa et al., 2023).

The use of AI-powered chatbots has also become widespread across many sectors, particularly in customer service, marketing, and the personalization of customer journeys. Retail and consumer services continue to be significantly influenced by the rapid advance of AI technologies, especially through AI-based chatbots which enhance customer experience through real-time interaction (Cheng et al., 2022). These tools are now integrated into omnichannel strategies, enabling companies to engage with their customers across multiple digital touchpoints (Huang & Rust, 2018; Patil & Kulkarni, 2019; Seitz et al., 2022). In various contexts, chatbots are perceived as effective and engaging substitutes for traditional services (Jiang et al., 2022; Miklosik et al., 2021; Sheehan et al., 2020; McLean & Osei-Frimpong, 2019). They notably enable companies to respond to information requests, resolve technical issues and improve service quality while reducing costs (Gnewuch et al., 2017).

Chatbots can replace human agents in tasks related to healthcare, finance, and customer service (Araujo, 2018) and although their adoption is increasing (Shumanov & Johnson, 2021), some consumers remain skeptical, still preferring human interaction (Roy & Naidoo, 2021). These systems are fully aligned with the logic of self-service, which is highly valued in the digital age. By automating interactions, chatbots can be conceptualized as self-service technologies (SSTs) (Doorn et al., 2017). However, the acceptability of these technologies varies depending on user profiles: some consumers, attached to human interaction, remain reluctant to adopt these tools (Collier & Kimes, 2013; Meuter et al., 2003).

At the same time, there seems to have been an interesting shift lately with people using chatbots like ChatGPT almost like a search engine. According to Statista (Gaudiaut, 2024), 24% of adults use generative AI to obtain information, including advice (10%), recommendations (6%) or to answer factual questions (11%). This puts these tools like ChatGPT in indirect competition with traditional search engines or product review platforms. The trend is even stronger among younger generations: in 2024, the 18–24 age group accounted for 46.7% of ChatGPT users, compared to only 24.7% for Google, indicating a growing preference for conversational agents in search behaviours (Statista, 2025).

This could show a potential shift in preference for chatbots when searching for information, hinting at a change in how people access information.

Yet, this technological shift brings out a fundamental concern. the phenomenon, known as the Google effect, described by Sparrow et al. (2011), demonstrates that individuals tend to remember more where information is available than the information itself when they know it is easily available online. This is closely related to the so-called digital amnesia, which is the tendency to forget about information outsourced to digital devices.

As Haenlein and Kaplan (2019)highlighted, AI is likely to become as omnipresent in our lives as the Internet or social media, therefore transforming how firms make decisions and interact with their stakeholders. This evolution raises some important questions about whether AI, humans or a mix of both should make certain decisions.

1.2. Problem statement

In a context where Artificial Intelligence is continuously gaining traction, particularly conversational agents such as generative AIs like ChatGPT, which has become very popular among the general public, the negative effects of these tools have not yet been fully examined from all angles. Indeed, their potential impact on certain cognitive processes remains largely unknown. The importance of examining this topic further is highlighted by their emergence in various fields and forms, including their use in marketing.

Currently, brands are relying more and more on these conversational agents in order to improve several aspects of their businesses, for instance in marketing, it can enhance the customer experience, drive engagement and improve overall customer satisfaction. However, these tools could affect the retention of information memory, which could also concerns brand and product-related information.

This thesis therefore aims to answer the following question:

Does reliance on conversational AI for product information searches influence consumers' unaided memory and to what extent is this relationship moderated by trust in the conversational agent and in the information it provides?

1.3. Research motivations

1.3.1. Managerial motivations

Despite the increasing integration of conversational agents into customer journeys, marketing literature focuses primarily on operational gains: automation, personalization, cost reduction and improved user experience (Huang & Rust, 2021). Yet another dimension is not yet fully explored: the cognitive effects of these technologies on consumers' memory.

The non-assisted memory, which is the ability to remember without external help, plays a fundamental role in building brand loyalty and retaining product information. Therefore, this research aims to study whether reliance on conversational agents for information retrieval could harm elements that shape the relationship between consumers and brands, such as brand memory, the knowledge associated with it and ultimately brand loyalty.

However, in a highly competitive market environment, brands are already facing many challenges to maintain and improve customer engagement and retention. They already need no to invest in differentiating strategies and impactful marketing initiatives sometimes. The rise of conversational AI makes this task even more complex, even more if it reinforces what is called digital amnesia. If AI were to reduce the ability of consumers to spontaneously remember brand-related elements, this would be an additional barrier that brands could overcome.

Thus, it is essential for marketers and managers to become aware of these new issues in order to design marketing strategies that, while allowing them to take advantage of the benefits associated with AI, could also limit its undesirable effects, especially on memory. For example, this could include thinking about how brands' chatbots are designed and used. It would be not only to facilitate access to information, but also to imagine interactions that promote the reactivation of user memory, in order to slow down or counter this tendency to cognitive delegation. It could also highlight the need for brands to keep a certain human presence in interactions with customers to try facing these limitations.

For brands, this could raise a strategic paradox: how to reach and stay in consumer’s mind, for the brand to be memorable in an environment where consumers could rely almost entirely on AI to access information?

Going a step further, the fact that consumers are turning to ChatGPT rather than search engines or official brand sites could lead to a loss of control over SEO and access to product information, as well as control over this information. This deviation from the traditional information journey could further weaken the relationship between customers and brands, limiting opportunities for direct contact, active engagement and therefore loyalty building.

This suggests that it could be strategic for brands to take these effects into account in their digital reflections: to hope to remain present in the minds of consumers, They would potentially benefit from a better control of their visibility on these new interfaces, while rethinking the design of their own conversational tools in order to limit or even compensate for memory externalization effects.

1.3.2. Academic motivations

While some experts praise the advances in artificial intelligence as a beneficial revolution, some remain more sceptical. During an interview with the BBC, in 2014, Stephen Hawking had already warning us about the risk that ‘’the development of Artificial Intelligence could spell the end of the human race’’ (Cellan-Jones, 2014) and also added in 2016 at Cambridge, that this technology could be "the best or the worst thing ever to happen to humanity" (University of Cambridge, 2016). Bill Gates pointed out in 2023 that the AI era had indeed begun, while also calling for an increased vigilance regarding its implications (Gates, 2023). These views, expressed by influential figures in the scientific and technological fields invite to reflect on the conditions for a balanced coexistence between humans and artificial intelligence, also regarding their potential harmful effects.

In this context, artificial intelligence has generated a lot of interest, for example in the marketing sector because of its promises of efficiency and personalization. However, little is known about how it affects consumers' cognitive abilities

According to Grewal et al. (2021), the potential negative effects associated with the use of these technologies are still poorly understood. Their widespread presence in several diverse fields such as education and health (Dergaa et al., 2023) points out the need for a thorough investigation. Therefore, examining these cognitive dimensions may help to at least partially bridge a significant gap in current research, and possibly in the filed of marketing.

The concept of cognitive offloading and the Google effect, as described by Sparrow et al. (2011), highlights individuals' tendency to outsource their memory by relying on information sources they easily have access to. While this effect has been documented in the context of search engines, it has not yet been thoroughly explored in relation to chatbots like ChatGPT. However, these tools, which are based on quite similar, if not more advanced, cognitive externalization's principles. Therefore, applying these theoretical foundations to conversational AIs could demonstrate the relevance of these theories in a technological environment that is even more immersive and interactive than before. Additionally, Tao, Zhang, and Liu (2024) introduced a scale measuring cognitive delegating to the IA, in creative processes, which illustrate the growing expansion of this phenomenon to AI.

Furthermore, the concept of transactive memory (Wegner, 1995; Ward, 2013) can be reviewed in the digital context by investigating whether users perceive ChatGPT as a memory partner. This could possibly allow the theory to be extended to human–AI interactions, paving the way for a new understanding of shared memory to reflect today's realities.

Finally, there is no current empirical study that has explicitly linked the use of AI nor ChatGPT to non-assisted memory for product information search. This gap represents an opportunity for academic contribution by exploring a perspective that remains unaddressed in the current literature.

1.4. Contributions

This research takes an exploratory approach to highlight a potential link between the use of AI-based conversational agents and consumers' unassisted memory, particularly in product information search.

Therefore, the objective of this work is not to establish a direct causal link but to observe first signals: this study seeks to explore to what extent this possible increased dependence on AI could thus influence the storage of related elements produced, which could also have potential consequences on brand awareness and loyalty.

At the managerial level, this research helps to identify what could become a new challenge for companies: the risk that cognitive outsourcing induced by conversational AI weakens the direct relationship between the brand and the consumer. Although the results do not aim to definitively validate these impacts, they make it possible to raise awareness among managers and marketers of this potential emerging problem. For example, it could be an incentive to rethink how chatbots are designed and the importance of maintaining human interactions with customers.

On the academic level, this research makes a first contribution on a subject still little explored in this field: the application of cognitive frameworks such as cognitive externalization or transactive memory to interactions between humans and generative AI. This study can thus serve as a starting point for further research, helping to identify relevant variables, possible effects and cognitive dimensions to be explored in increasingly interactive digital environments.

In conclusion, this work does not aim to draw definitive conclusions but rather to open the way for researchers and professionals alike on the possible cognitive implications of conversational AI in marketing.

1.5. Approach

This study aims to explore the potential impact of the use of conversational artificial intelligence on consumers' unaided memory, more specifically regarding product-related information.

Thus, the study begins with an analysis of the current digital context and is built around a review of the existing literature, allowing for the definition of key concepts such as digital amnesia or the Google effect, as well as the identification of existing contributions and limitations in the literature. Based on this review, several hypotheses were developed and a model was proposed in order to attempt to identify a potential impact of the use of such agents on memory retention.

On this basis, a questionnaire was designed, including a short experimental task, in order to collect quantitative data allowing for the measurement of the defined variables. To test this possible effect, the study focuses more specifically on ChatGPT, which is currently one of the most widely used AI-powered chatbots.

Then, an analysis of the collected data makes it possible to test the different formulated hypotheses and to examine the existence of an impact or a link between the studied variables. Following that, the results are discussed and interpreted in light of the existing literature.

Finally, in the last part of this research highlights its managerial and theoretical implications, as well as its potential limitations and suggestions for future studies on the topic are also provided.

II. Literature Review

2.1. Literature Review

2.1.1. Artificial Intelligence

Artificial Intelligence (AI) refers to a set of system designed to stimulate certain human cognitive functions, such as learning, problem solving or understanding natural language (Syam & Sharma, 2018) and has the ability to improve itself from data, using machine learning algorithms without requiring human intervention (Huang & Rust, 2018 ; Haenlein & Kaplan, 2019). From devices, such as robots, drones, recommendations systems, voice assistants or chatbots, which are able of collecting data then analysing it to extract meaning and adjust their functioning in order to achieve specific objectives. Therefore AI can execute much faster some specific and structured tasks than human intelligence, traditionally more generalist and flexible (Vaccaro et al., 2024 ; Melville, Robert & Xiao, 2023).

In the marketing field, AI has considerably changed the way companies interact with their consumers, notably allowing them to personalize customer experiences, better analyze behaviors, anticipate future needs and optimize strategic decision (Haleem et al., 2022; Huang & Rust, 2021). Overall, AI applies to areas such as product recommendation, price optimization, facial recognition, customer service automation and natural language processing to engage consumers (Ablanedo-Rosas et al., 2021; Huang & Rust, 2021). Among these applications, the automation of customer service through chatbots plays a central role, supporting companies in managing their interactions with consumers and making exchanges more efficient and responsive (Murtarelli, Gregory & Romenti, 2021).

This great ability for analysis allows companies to interpret very large volumes of data instantly, promoting both commercial and decision-making responsiveness (Haleem et al., 2022).

Consumers are also immersed in a dense digital environment, where speed, fluidity and personalization are basic expectations and the growing adoption of AI-based conversational technologies and with it the rise of chatbots and voice assistants, is moreover well underway in the majority of the customer journeys. These communication agents facilitate quick access to relevant product information for the user, thereby reducing the need for complex manual searches (Verma et al., 2021). By automating certain support activities in addition to simplifying human interaction, they indeed foster greater consumer engagement and enhance marketing efficiency (Verma et al., 2021; Wisetsri et al., 2021)

Several concrete applications support both the realized and anticipated benefits of AI and its expected gains in marketing efficiency and optimization. This can be illustrated, in particular, with examples in a B2C context, such as IBM Interact, which enables personalized offers at the Bank of Montreal, Amazin GO, which leverages AI to automate payment or even with vee24's nudging bots, which accompany consumers throughout their purchasing journey (Davenport et al., 2020 ; Davenport et al., 2021 ; Guha et al., 2021).These types of applications highlight the full potential of AI to redefine corporate strategies and consumer practices.

AI is no longer limited to technical functions in the background but has now become a direct interaction agent in company-consumer relationships, influencing user experience, customer satisfaction and brand perception alike (Huang & Rust, 2021; Murtarelli, Gregory, & Romenti, 2020).

2.1.2. Conversational agents and AI-powered chatbots

Chatbots, also referred to as conversational agents (Kerly et al., 2007), are software programs designed to simulate a conversation that a human user might engage in using natural language, whether written or spoken (Adamopoulou & Moussiades, 2020). They exist in two forms: textual chatbots, which interact through instant messaging platforms (Rese et al., 2020), and voice chatbots, which communicate through speech, such as Siri, Alexa or Google Home (Lim et al., 2022; Ling et al., 2021).

There are currently two main categories of chatbots: rule-based chatbots, which operate solely on the basis of predefined scenarios and can only respond to specific types of predefined queries (Hingrajia, 2023) and chatbots powered by artificial intelligence and natural language processing techniques, which are capable of handling more complex tasks. Chatbots powered by artificial intelligence and natural language processing (NLP) technologies enable the system to understand and generate responses in human language, thereby reproducing a smooth conversational interaction by imitating human dialogue (Khadija et al., 2021; Pantano & Pizzi, 2020; Yen & Chiang, 2021). These conversational agents also use machine learning techniques, which allow them to improve themselves over the course of interactions (Ling et al., 2021; Mariani et al., 2023; Kang & Choi, 2023).

Conversational agents, more particularly chatbots, are gradually beginning to establish themselves as essential tools in many economic spheres, especially retail, health, finance and also education (Feine et al., 2019; Lalicic & Weismayer, 2021; Larivière et al., 2017; Mariani et al., 2023). The communication features offered by these dialogue systems, thanks to advances in the field of artificial intelligence, mean that users can communicate naturally, in human conversation (Yen & Chiang, 2021), covering services ranging from personal assistance to information and entertainment (Brandtzaeg & Følstad, 2017). Their growing deployment is justified by notable advantages such as permanent availability, speed of response, efficiency in terms of resources and customer service costs (Radziwill & Benton, 2017; Hill et al., 2015; Nordheim et al., 2019). Moreover, the rise of intelligent chatbots is also based on their ability to improve productivity and perceived efficiency for users. It has been shown (Brandtzaeg et al., 2017) that users primarily seek access to information or to request effective assistance.

In this dynamic, text-based chatbots prove to be particularly present in digital journeys, with strong integration in a large part of companies that focus on managing customer requests (Chung et al., 2020; Jang et al., 2021; Rese et al., 2020; Pantano & Pizzi, 2020). Chatbots are often integrated into digital assistants, where they play a central role in automating customer interactions, thus reducing the need for direct human intervention (Pantano & Pizzi, 2020; Gnewuch et al., 2017). Designed as virtual agents, they aim to solve problems, assist users, provide advice in an automated way or guide decisions (Tintarev et al., 2016; Chung et al., 2020). This ability to occupy multiple functions becomes concrete in e-commerce, where chatbots can participate in navigation, answering frequently asked questions, recommending products, or facilitating transactions (Mariani et al., 2023; Kim et al., 2022; Moriuchi et al., 2021). Thus, they perform a function of digital intermediaries able to repeat a quality customer interaction without the use of delays associated with human intervention (Rese et al., 2020; Roy & Naidoo, 2021).

In the context of marketing, the use of chatbots enables brands to rethink and renew the relationship between them and their clients. Intelligent conversational agents support the customer experience proposition, that is smooth, fast while also being more personal, facilitated by the ability to make recommendations, to answer a question instantly, to accompany (Prakash et al., 2023; van der Goot et al., 2021). They constitute an integral part of omnichannel strategies as an always accessible point of contact, at any time and in any place (Yen & Chiang, 2021). Within companies, Misischia et al. (2022) name their main applications in sales functions (41%), support (37%), and marketing (17%) across several sectors, thereby highlighting their role in customer relationship management.

In the context of digital marketing, chatbots fall within a logic of substitution or complementarity to human agents, by allowing companies to better manage the volume of requests while maintaining a satisfactory level of quality in exchanges (Huang & Rust, 2021, 2022; Ruan & Mezei, 2022), since they intervene from the first contacts to bring out consumer needs, guide their choices, and thus contribute to the enrichment of the user experience (Prentice et al., 2020). A study by Chung et al. (2020) shows that such a system can have a positive impact on customer satisfaction by promoting a high level of engagement in the service offered and in its interactive dimension. Chatbots can thus be used not only as levers of operational efficiency, but also as strategic tools generating marketing value focused on customer loyalty, enhancing the user experience, and brand image (Camilleri & Troise, 2022; Suhel et al., 2020).

Despite the remarkable rise of conversational agents in various sectors, research on their use in the shopping domain is mainly centered around specific areas. Existing studies have primarily focused on customer satisfaction, thus overlooking other relevant dimensions (Jiang et al., 2022; Ruan & Mezei, 2022). At the same time, while chatbots have attracted growing academic interest (Rese et al., 2020; Jenneboer et al., 2022; Chen et al., 2022), the literature is largely oriented toward topics such as user intention to adopt or continue using these technologies in various decision-making contexts (Baek & Kim, 2023; Liu & Ma, 2024).

Several recent studies have also examined how chatbots can help strengthen brand loyalty, particularly through the perceived quality of the service they provide (Ittefaq et al., 2024; S. Zhang et al., 2022), including in sector-specific cases such as tourism (Y. Zhu et al., 2023). Interactions perceived as reliable can enhance trust in the brand, thereby fostering loyalty (Hsu & Lin, 2023; Jenneboer et al., 2022).

Another line of research explored in the literature is chatbot anthropomorphism, that is, the attribution of human characteristics to these agents, an approach aimed at making them more familiar or appealing. This humanization has been shown to have positive effects on user behaviour, such as increasing conversion rates or usage intention (Schanke et al., 2021; Blut et al., 2021).

Despite this thematic diversity, most existing research tends to focus on optimizing chatbot effectiveness, whether by understanding why they work, how to improve their use, or how to leverage them to enhance marketing metrics like loyalty and engagement. To date, however, no research appears to have examined the effect of AI-powered chatbots on consumer memory, even though this is a central factor in shaping experience and purchase behaviour.

2.1.3. The case of ChatGPT: a turning point in chatbot usage

Launched in November 2022 by OpenAI, ChatGPT marks a crucial milestone in the evolution of conversational agents, particularly due to its ability to understand and formulate statements or discourse in everyday language in a contextual, fluent, and nuanced manner (OpenAI, 2022; Lund & Wang, 2023). Built on the architecture of Generative Pre-trained Transformers (GPT), it relies on a language model trained on vast textual data, capable of producing responses that closely resemble human language (Dale, 2021; Dwivedi et al., 2023; Lund & Wang, 2023). This technological breakthrough has significantly enhanced chatbot performance, endowing them with a far more natural and engaging conversational quality.

The popularity of ChatGPT has surged dramatically since OpenAI made its interface freely available: its growth set a record, with over one million users in five days and one hundred million two months later (OpenAI, 2022). It is a tool capable of handling complex requests and generating contextual, detailed, and non-predetermined responses, as it has been trained on large text datasets (Lund & Wang, 2023; OpenAI, 2022). Furthermore, through learning based on user interactions, ChatGPT continuously improves the relevance of its responses (Haque et al., 2022), allowing it to perform far better than conventional chatbots. This technology has thus revolutionized the chatbot industry by providing businesses with a sophisticated tool for interacting effectively with their clients.

These diverse applications partly explain why ChatGPT has quickly established itself as a strategic tool for businesses. It can notably generate personalized content, contributing to a more engaging user experience, particularly in marketing and customer relations (Gupta et al., 2024). Key indicators of itd anticipated benefits include reduced costs and turnaround times (Dumrak & Zarghami, 2023; Yaiprasert & Hidayanto, 2024), enhanced productivity (Wamba-Taguimdje et al., 2023), improved customer experience (Kumar et al., 2021), and enriched knowledge through new avenues of exploration, making it a strategic asset in addressing emerging challenges across various sectors.

Finally, its capabilities and applications are being deployed across various fields such as education (Kabudi et al., 2021; Kasneci et al., 2023), customer service (Camilleri & Troise, 2022), and e-commerce (Moriuchi et al., 2021). ChatGPT is also used as a virtual assistant or conversational tool in a wide range of applications that rely on natural language understanding and generation (King, 2023; Cascella et al., 2023; Deng & Lin, 2022). As a generative tool, it can produce text, rephrase content, draft emails, or provide on-demand information (Salvagno et al., 2023). Its use now extends to diverse domains such as healthcare (Shen et al., 2023), legal writing (Shope, 2023), cybersecurity (Mijwil & Aljanabi, 2023), programming (Avila-Chauvet et al., 2023), and entertainment (Aydin et al., 2023).

While some already regard ChatGPT as a leading public-facing AI chatbot (Roose, 2022; OpenAI, 2022), others express concern about the potentially harmful impacts of the very tools they have developed, for instance regarding the future of work (Krugman, 2022) and ethical issues already raised by Cotton et al. (2023). The question of ChatGPT's place in society and industry is sparking a growing and nuanced debate.

The discussions surrounding its societal role reflect concerns within the academic sphere. Numerous obstacles hinder its adoption in this domain, particularly given that one of the main limitations lies in the quality of its training data: if the data is biased or incomplete, the generated responses may be inaccurate (Liebrenz et al., 2023). Added to this is the lack of transparency in how ChatGPT operates, with its decision-making processes remaining largely opaque and difficult to interpret (Patel et al., 2023).

Recent advances in AI-based conversational interfaces, such as ChatGPT, are also generating growing interest in the field of education (Kasneci et al., 2023; Rudolph et al., 2023). In this context, several studies have examined the factors influencing user experience with these technologies (Choudhury & Shamszare, 2023; Shahsavar & Choudhury, 2023; Menon & Shilpa, 2023; Foroughi et al., 2023). However, most of these studies focus solely on users' initial intentions to adopt them.

2.1.4. How ChatGPT shapes memory and mental effort

The growing rise of ChatGPT as a tool for information retrieval, decision-making, or writing assistance raises serious questions about memory and cognitive processing. As noted by researchers Skjuve, Brandtzaeg, and Følstad (2024), more than one in two users report using ChatGPT to improve their productivity, particularly due to the ease of information extraction it offers. In fact, the "facilitated search" function is the highest rated: 67% of respondents believe that ChatGPT helps them understand complex queries and provides satisfying answers. This immediate and efficient accessibility makes ChatGPT a serious competitor to traditional search engines (Friedman, 2022). Its function as a daily information management tool is expanding (Friedman, 2022). In this regard, Yankouskaya et al. (2024) observe that this use primarily allows users to save time and make more informed and therefore faster decisions. This benefit is especially valuable in a saturated digital environment where information is abundant and sorting, prioritizing, and making sense of it is challenging.

In this context, the use of AI-based chatbots in our daily lives raises discussions about their impact on mental health (Bai et al., 2023). Delegating certain tasks to these tools comes with consequences. Many people observe that, although convenient, using ChatGPT can also encourage a certain intellectual laziness and reduce our engagement in memory processes (Menon & Shilpa, 2023). This echoes studies on information overload: the more a tool takes care of selecting, organizing, and analyzing data, the less we are likely to retain that information in the long term (Chandler & Sweller, 1991; Bai et al., 2023).

Cognitive load theory, in particular, can help shed light on this dynamic. When interacting with conversational agents, these tools can make things easier by organizing information and offering ideas. At the same time, however, they may also require additional effort, as users must properly formulate their questions, assess the responses, and determine how these align with their existing knowledge or goals (Choudhury & Shamszare, 2023). Moreover, interacting with these tools differs from engaging with traditional information sources. Because they respond directly and interactively, they can significantly increase user trust and influence cognitive processes differently than traditional search engines (Adamopoulou & Moussiades, 2020).

Danaher (2018) raises a critical concern: even though AI assistants free up mental time for more important tasks, this does not necessarily mean that we will use that time for activities that truly engage our brains. In fact, excessive delegation can even lead to what is referred to as "cognitive degeneration," where our memory and understanding weaken simply because we rely less on our natural abilities.

By facilitating access to structured and contextualized content, ChatGPT optimizes task performance but may also lead to a reduction in active memory engagement. This phenomenon, known as cognitive offloading, is well documented in research on the Google effect (Sparrow et al., 2011). Instead of remembering the information itself, people tend to remember where and how to retrieve it.

Current studies on the use of ChatGPT also confirm this trend. The user experience of ChatGPT is characterized by a level of trust in the tool's perceived sufficiency, which is linked to a form of cognitive appropriation leading to the tool becomes a reference point and assists users in meeting their needs intuitively and efficiently. However, this high level of trust in the tool may reinforce a form of passive reliance, in which the user stops actively engaging their analytical and memorization skills.

In conclusion, while the ChatGPT tool offers a notable gain in efficiency and accessibility of information, regular use could transform the cognitive processes of encoding, storing, and recalling information by altering cognitive load. This shift in cognitive load, combined with strong trust in the technology, represents a still underexplored area of research, but one that could be central to better understanding the cognitive effects of next-generation conversational agents.

2.1.5. Memory retention in the digital age

Memory in the Digital Age: between overload and externalization

The evolution of digital technologies seems to have affected human memorization processes. In today's connected world, where information is made accessible anytime and everywhere, information overload is increased by the generalization of digitalization practices (Arnold Goldschmitt & Rigotti 2022). In this new information-saturated environment, the cognitive mechanisms of retention, encoding and retrieval of information change are altered, especially when individuals externalize these memory functions which belong to their cognitive abilities through technological tools like conversational agents.

The concept of digital amnesia was first introduced by Kaspersky Lab (a company specializing in cybersecurity) in 2015, which refers to "the experience of forgetting information you entrust to a digital device to store and remember for you" because of the growing tendency to forget information we entrust to digital devices, such as the smartphone and voice assistants.

In a pioneering study, Sparrow, Liu and Wegner (2011) showed that individuals who expect that information will be saved (and which is now within reach, for instance in a computer file) are less likely to retain it. This series of experiments suggested a redirection of human memory: individuals tend to remember where the information is located rather than the information itself. In other words, the simple fact of knowing that the information will be available later is enough to reduce the memorization effort. This phenomenon known as the Google effect illustrates that the Internet acts as an external amnesic partner changing the dynamic between internal memory and memory stored outside the body.

These results have been confirmed and qualified in several research conducted later. Schooler and Storm (2021) for instance tried to replicate the Google effect while exploring another condition: the perceived reliability of the storage support. Their results show that the Google effect tends to occur if participants believe in the reliability of the digital storage support. Without this belief the Google effect weakens. According to this study, the conviction in the future accessibility of the information appears to be a key factor in the reduction of memory encoding.

In their study, Fisher et al. (2019) showed on how online searching influences people's self-perceived knowledge that individuals had the impression of having acquired knowledge after simply searching for it online even though the information had not been truly memorized. In this regard, Ward (2013) had already pointed out that accessing information through a familiar platform, such as Google for example, can give the impression of direct access to information because the tool is perceived less as an external aid and more as a partner. These findings help explain how digital tools can shape both memory and users' perception of what they know.

This cognitive externalization is part of the transactive memory theory (Wegner 1995), according to which, in a couple or a group, individuals build a shared memory (and shared by the partners) and each person knows "*who knows what*". In the case of the Internet, the digital tool replaces this partner. Thus, Wegner (1995) points out that this dynamic can make it difficult for individuals to distinguish between the knowledge they possess and the knowledge they believe they possess simply since it is accessible through a partner or in this case, a machine.

Cognitive Offloading

The principle of cognitive externalization, also called cognitive offloading, is described as the use of a physical action to modify the information processing demands of a task and to initiate a reduction of cognitive effort according to Risko and Gilbert (2016). Examples of these tasks might include the activities of taking notes, setting an alarm, or searching online for information.

The use of the Internet and digital tools clearly emerges as one of these means. In this sense, several studies observe the immediate benefits of cognitive offloading. Grinschgl, Papenmeier and Meyerhoff (2021) show that externalization increases short-term performance, as tasks are done faster and better. Cognitive resources are thus better freed from simple tasks to focus on more complex ones. This mechanism is considered an adaptive strategy when the cognitive load is required beyond the capacities of working memory.

Nevertheless, this cognitive externalization has a cost. The more it is practiced over time, the more it impairs our internal memory, especially the externalized information (Risko & Gilbert 2016; Grinschgl et al. 2021). In other words, what is entrusted to an external device is less well-encoded and therefore, less well-retained. The more the individual externalizes, the faster the task can be completed, but this happens at the expense of information retention (Grinschgl et al. 2021). This trade-off between instant efficiency and lasting memory is a central tension highlighted by contemporary research.

Digital Amnesia

In addition to laboratory research, large-scale empirical studies also help to stay aligned with the social dimensions of digital amnesia. According to a report by Kaspersky Lab? after surveying several thousand European respondents, more than 90% of the individuals questioned use the Internet as an extension of their memory and one third of them considered their smartphone as their main memory. These studies show that consumers now use digital tools to store all types of personal information such as phone numbers memories to-do lists etc. Only 21% of respondents still rely on their own memory to retain information the vast majority prefer depending on electronic reminders notes on their phone or sending emails to themselves depending on the case. The study also reveals an ambivalent feeling for some it is a way to focus on what matters for others it is a source of concern especially in case of data loss.

These results are supported by the study of Musa et al. (2023), which shows that the use of digital tools is accompanied by greater difficulty in retaining information without these devices. Their ability to build knowledge independently is reduced and they show an increased tendency to rely on existing sources rather than actively process information. Similarly, Kanbay et al. (2025) suggest that this technological dependence has negative effects on memory retention, especially among younger generations.

Finally, the results of Nagam (2023) shed light on interactions from the perspective of the dynamics that govern semantic memory and transactive memory. The conducted experiments showed that activating transactive memory (for example, searching for information directly on the Internet) reduces the possibility of encoding this information into semantic memory by allowing only superficial cognitive processing. Semantic memory refers here to long-term declarative memory of general facts and data and includes cultural knowledge ideas and concepts accumulated throughout one’s lifetime. Conversely, an initial effort to retrieve information from semantic memory then supports the activation of both systems. As a result, Internet users may either strengthen or weaken their internal memory depending on the order in which they activate these cognitive systems. In other words, when people first try to recall the “what” (the content of the information) they are more likely to remember both the “what” and the “where” (the location of the information), or at least the “what”, whereas when they first try to recall the “where”, they most often remember only the “where” or neither.

Taken together, these findings highlight how the growing reliance on digital technologies reshapes the way individuals manage, store and recall information, raising important questions about the long-term effects on cognitive functioning and memory autonomy.

2.1.6. Conversational AI and memory retention

Although the research literature on the cognitive implications of digital technologies is increasing and in particular on how the Internet and search engines affect human memory (Sparrow et al., 2011;

Ward, 2013; Schooler & Storm, 2021), the effects of AI-based conversational agents remain largely underexplored, especially in applied usage contexts such as online commerce or product information search. Gupta et al. (2022) show that conversational interfaces enhance trust and satisfaction in decision support systems, but their study did not examine deeper cognitive implications such as the process of memorizing information, thus leaving it largely unexplored.

The cumulative evidence from previous research (Cognitive offloading; technological transactive memory (Firth et al., 2019; Risko & Gilbert, 2016) mostly in controlled experimental settings, draws attention to instances of cognitive underpinnings (e.g., cognitive offloading; technological transactive memory; metacognitive biases). However, few studies have explored how these cognitive mechanisms translate to interactions with conversational tools like ChatGPT, which are more accessible, customizable, and linguistically sophisticated.

In this perspective, authors such as Bai et al. (2023) and Adamopoulou & Moussiades (2020) note that the direct and interactive nature of AI agents could lead to an even greater degree of cognitive reliance than traditional search engines, affecting the ability to memorize independently and to actively mobilize knowledge.

Most studies on generative AI and conversational agents focus on variables related to usage, behavioural intention, and user satisfaction (Baek & Kim, 2023; Choudhury & Shamszare, 2023; Jan et al., 2023), without addressing the deeper effects these technologies may have on consumers' cognitive processes, particularly in decision-making situations involving practices such as shopping or evaluating a commercial offer.

In addition, a recent meta-analysis conducted by Vaccaro et al. (2024), examining 106 experimental studies, concludes that among generative AI studies involving human participants, the majority focus on self-reported attitudes and preferences. In contrast, few studies address cognitive processes such as memory or the mental effort required during interaction.

The work of Grewal et al. (2021) indeed highlights an imbalance in the literature, which places strong emphasis on the operational and marketing benefits of AI, while overlooking potentially negative effects, particularly in terms of trust, delegation of autonomy, or the erosion of certain cognitive abilities. This observation is especially concerning in a context where the widespread integration of chatbots (OpenAI, Meta, Google, DeepMind) into the customer journey is increasingly becoming the norm.

Finally, the research conducted by Gupta et al. (2024) highlights the lack of conceptual clarity regarding the consequences of using conversational agents for marketing purposes: despite relatively rapid and widespread adoption, there is still uncertainty about their actual impact on consumers' decisions and cognitive operations.

In sum, several major gaps emerge:

- The absence of empirical studies linking the use of conversational AI, such as ChatGPT, with unaided memory in a marketing context.
- The lack of research explicitly drawing on cognitive frameworks, such as cognitive load theory, in the analysis of human-AI interaction involving artificial intelligence-based conversational agents.

This research primarily aims to evaluate reliance on conversational AI, such as ChatGPT, and its potential impact on non-assisted memory, by incorporating trust as a mediating variable. By seeking to connect concepts from fields that have so far remained largely unlinked, it aims to bridge certain theoretical and empirical gaps regarding the cognitive effects of conversational agents.

2.2. Model

2.2.1. Non-assisted memory

Non-assisted memory refers to an individual's ability to encode, store, and retrieve information without relying on external aids, such as a search engine or a conversational agent. In the context of this research, it is considered an expression of autonomous memory, as opposed to transactive memory, which occurs when the user delegates information processing to an external technological source.

This concept is closely linked to research on cognitive offloading (Risko & Gilbert, 2016) and the Google Effect (Sparrow et al., 2011), which highlight a tendency to reduce memorization effort when information is perceived as being readily accessible. In such cases, users tend to remember the location of the information rather than the information itself. Studies further show that this externalization can lead to an illusion of knowledge, making it difficult for individuals to accurately judge whether they have actually retained the information, simply because it was accessed through a digital device (Fisher et al., 2022; Ward, 2013).

This dynamic is supported by the metacognitive model of offloading (Dunn & Risko, 2016), which posits that individuals choose to delegate memorization based on a subjective evaluation of cognitive costs. When memory load is perceived as high, individuals tend to favor externalization, which in turn reduces deep encoding.

In the context of conversational AIs, particularly ChatGPT, this issue is amplified by the tool's linguistic fluency and constant accessibility. By reducing the cognitive effort required to understand or structure information, such systems may decrease the engagement of endogenous memory.

Non-assisted memory is thus used as the dependent variable to assess the impact of regular and perceived-as-reliable use of conversational agents on individuals' ability to autonomously remember information obtained through AI. Adamopoulou and Moussiades (2020) emphasize that the immediacy and contextualization of responses provided by such systems reinforce delegated memorization, making the activation of internal memory less necessary.

This choice is also supported by recent empirical findings showing that cognitive delegation to such tools leads to a decline in memory retention, particularly when users trust the AI to provide reliable and instantaneous answers (Musa et al., 2023; Kanbay et al., 2025; Nagam, 2023). As such, non-assisted memory serves as a key indicator for assessing the effect of intensive and trust-based use of AI on internal retention capacities in the context of product information search.

2.2.2. Reliance on Conversational AI

In the context of this research, reliance on conversational AI is defined as the degree to which a user depends on an AI conversational agent to access information. It is structured around two complementary dimensions: frequency of use and perceived convenience. These two dimensions reflect how users engage with such tools to reduce cognitive effort and externalize certain mental functions.

On the one hand, frequency of use refers to how habitually consumers rely on conversational agents to search for brand- or product-related information. In the field of chatbots, Jan et al. (2023) show that frequency of use is driven by factors such as ease of use, perceived usefulness and interactivity, fostering a habitual use that can evolve into routine reliance. Menon and Shilpa (2023) confirm that users view ChatGPT as a fast and centralized tool capable of immediately addressing a wide range of needs, thereby encouraging frequent use and functional dependency. Sallam et al. (2023), for their part, warn against the risk of overusing ChatGPT, which may lead to a form of "cognitive apathy," where users stop questioning the answers provided. Dwivedi et al. (2023) also highlight that the ease of access to information through simple interfaces increases usage frequency, potentially resulting in behavioural dependence.

On the other hand, perceived convenience refers to the belief that using AI enables quick, easy, and effortless access to information. This concept aligns with the notion of perceived ease of use, defined as "the degree to which a person believes that using a system would be free of effort" (Davis, 1989). This perception of convenience, which is directly linked to the notion of accessibility (Swanson in Davis, 1989), encourages both the adoption and the habitual integration of the technology into everyday practices. Several studies (Davis, 1989; Ko et al., 2005) have demonstrated that the more a tool is perceived as "convenient," "simple," or "unobtrusive," the higher the likelihood of its acceptance and frequent use. Adamopoulou and Moussiades (2020) further note that the interactive dynamic inherent to conversational AIs fosters a specific form of cognitive reliance, distinct from that associated with static sources of information, by reinforcing the habit of offloading memory-related tasks.

Alshammari and Babu (2025) state that perceived ease of use, while not affecting usage intention directly in all contexts, has a substantial effect on user satisfaction, which subsequently acts as a mediator toward use intention. Thus, a tool that involves perceived ease of use and availability, for instance ChatGPT, will be used more often and automatically, perhaps even indicating some level of implicit dependence.

Zhai (2024) builds on this reflection by highlighting that the overuse of conversational agents can weaken essential cognitive functions such as critical thinking, analytical capacity, and autonomous decision-making. Although conducted in an academic context, these findings can be extended to the consumer domain. The pursuit of quick information, facilitated by an interface perceived as efficient, encourages the use of cognitive shortcuts at the expense of deeper content processing. In this sense, while AI can support personalized and streamlined interactions, excessive reliance may undermine cognitive engagement and impair long-term information retention (Bai et al., 2023). This preference for speed and ease may thus reinforce reflexive consultation behavior rather than active cognitive engagement. Baird and Maruping (2021) emphasize that the more AI-generated responses appear natural and human-like, the more users tend to overly rely on them in their decisions, reinforcing a pattern of delegation.

In the context of this research, these two dimensions, frequency and convenience, are used to operationalize reliance on conversational AI as an independent variable likely to negatively affect non-assisted memory. Indeed, several studies (Yankouskaya, 2024; Ahmad et al., 2023) converge on the idea that delegating cognitive tasks to AI, especially when it is perceived as effortless—promotes a form of cognitive passivity that can lead to a decline in active memorization and an overreliance on the machine.

- **Hypothesis (H1).** The higher the reliance on conversational AI (measured by usage frequency and perceived convenience), the lower the unaided memory of brand-related information.

2.2.3. Trust

Trust plays a key role in interactions between individuals and technological systems, significantly influencing their acceptance, use, and cognitive impact (Van Pinxteren et al., 2019; Cukurova et al., 2023; Kaplan et al., 2023). In the context of this research, trust in conversational AI is considered a mediator between reliance on AI and non-assisted memory capacity.

More specifically, the literature distinguishes two relevant forms of trust in this context: trust in the system itself (e.g., ChatGPT), and trust in the quality of the information it provides. Both dimensions influence how users engage with the tool and cognitively evaluate the content they receive (Shahzad et al., 2024; Baek & Kim, 2023).

Trust in conversational AI

Numerous studies show that trust in chatbots is a prerequisite for their acceptance and repeated use. According to Siau and Wang (2018), this trust applies not only to the technology itself, but also to its use and perceived purpose. In the context of conversational AI, this means that the more a user perceives the system as reliable, the more likely they are to delegate cognitive tasks, such as searching for, evaluating or selecting information (Afroogh et al., 2024; Shahzad et al., 2024).

Adamopoulou and Moussiades (2020) point out that the interactive and immediate nature of conversational agents fosters a stronger form of trust than that typically granted to traditional search engines, which may in turn reinforce cognitive reliance mechanisms.

Menon and Shilpa (2023) nuance this trend: although ChatGPT's user-friendliness is widely appreciated, some users express doubts about the reliability of its responses, highlighting the need to consider trust as an independent and contextually modulated variable. Cheng et al. (2021) add that the complexity of the tasks to be performed can weaken the influence of perceived friendliness and empathy on trust, showing that trust is neither uniform nor constant.

Finally, M., P. V. S. and Kryvinska (2024) show that initial trust in the chatbot acts as a mediator between perceived ease of use and usage intention, while also being influenced by users' age, a dimension explored in this study as a moderating variable.

Trust in the information provided

In parallel, the perceived quality of the information generated by the chatbot is a key factor in the process of content appropriation. Chung and Park (2019) emphasize the role of perceived accuracy and relevance of the information, which determine the overall evaluation of the service and the intention to reuse it. Similarly, Alagarsamy et al. (2023) show that trust in the information directly influences the customer experience and usage behaviours.

C.Y. Li et al. (2023) observe that perceived reliability of AI in handling personal data and solving problems helps build a relationship of trust, which in turn shapes brand perception and promotes digital loyalty. Likewise, Ruan and Mezei (2022) highlight the importance of consistent AI performance: the stability of responses, regardless of context, strengthens users' long-term trust.

This trust in the responses leads to reduced doubt, which may cause individuals to avoid actively encoding the information or verifying its accuracy, a process that Zhai (2024) refers to as passive delegation, in which the fluency and speed of the interaction mask the absence of deep processing. This mechanism can affect non-assisted memory, since personal validation and active encoding are fundamental conditions for information retention.

Moreover, this dynamic can also be explained through metacognitive models of cognitive offloading (Risko & Gilbert, 2016), which suggest that decisions to delegate a cognitive task, such as remembering information, depend on subjective evaluations of reliability and perceived usefulness, in other words, trust in the tool.

A Cognitive Mediation

Trust in the chatbot and in the information it provides functions as a cognitive bridge: it enables reliance (i.e., frequency of use and perceived convenience) to influence non-assisted memory. When trust is high, users perceive the tool as sufficiently reliable, making it seem unnecessary to actively store the information. In contrast, low trust may encourage users to verify, compare, or retain the content more actively, which in turn reinforces cognitive engagement.

This mediating role is particularly important given that, in classical models of technology acceptance (TAM, UTAUT), trust acts as a catalyst between perceptions of the tool and usage behaviors (Siau & Wang, 2018). In an environment of information overload, trust becomes a powerful heuristic for assessing the validity of information, often at the expense of critical analysis.

- **Hypothesis (H2).** Trust in conversational AI and in the information it provides mediates the relationship between reliance on AI and unaided memory, such that a high level of trust amplifies the reduction in unaided memory associated with chatbot use.

2.2.4. The moderators

The complexity of the information

Among the contextual factors that could influence the relationship between reliance on conversational AI and unaided memory, the complexity of the information searched for may serve as a potential moderator. From a theoretical standpoint, perceived complexity can act as an amplifier of reliance, increasing the likelihood that users will delegate tasks of comprehension, analysis, and memorization to the system. This dynamic may be particularly relevant in product information search contexts, where the volume and technicality of criteria to evaluate can easily overload an individual's working memory.

The available literature on cognitive offloading shows that individuals tend to externalize their cognitive functions more when the task at hand is perceived as cognitively demanding, particularly in terms of working memory load or difficulty of understanding (Risko & Gilbert, 2016). This delegation is stronger when the information to be processed is considered difficult due to its perceived complexity. In other words, the more complex a task is, the more likely individuals are to neglect the effort of autonomous memorization in favour of technological support.

Cheng et al. (2022) note that task complexity can also have a direct impact on consumer perceptions of the relevance and usefulness of a conversational agent. If the requested information is considered more complex, (for example, comparing two technical products), then the user will expect only expert, precise and contextualized responses from the chatbot. A friendly or standard response is no longer enough, resulting in an increased reliance on AI to manage uncertainty and maybe an even decreased cognitive engagement on the part of the user.

- **Hypothesis (H3).** The complexity of the information searched moderates the relationship between reliance on conversational AI and unaided memory, such that more complex information leads to increased reliance on AI and, leading to a more pronounced reduction in unaided memory.

The age

Age was considered in this study as a moderating variable because of its influence on the cognitive effects related to the use of conversational AI especially concerning memory retention and the way individuals rely on these technologies to either remember or forget information particularly related to products. Many of the studies conducted on the subject are based on samples with young adults usually students involved in the use of ChatGPT in academic settings (Alshammari & Alshammari, 2024; Shahzad et al. 2024). The results show that perceived ease of use and trust support repeated usage which may be a sign of cognitive delegation. But the restriction to younger people leaves the question of generalizing the effects to other age groups unresolved.

In this sense age is used here as a moderator of the link between reliance and memory without assistance since the cognitive effects of interaction with AI could depend on generations. The overall data from two separate surveys illustrate this diversity of use. On one hand, 61% of global ChatGPT users are between 18 and 34 years old with especially 25–34 years at 33% and 18–24 years at 28% so the generational group is clearly marked in the young adult category while Google shows a more balanced use which would indicate a generational shift in tools for accessing information. While 18–

24 year olds represent 47% of ChatGPT users compared to only 24% for Google on the contrary people aged 35 and over are proportionally more represented among Google users. These figures show that young adults seem to choose ChatGPT over search engines like Google and reveal a difference in the use of technologies which could lead to diverse cognitive behaviours in terms of memorization or delegation to the tool.

On the other hand, another study conducted by Semrush and also reported by Statista (2025) indicates that nearly 47% of global ChatGPT users are in the 18–24 age group while the share of users decreases sharply with age reaching only around 4% for those aged 65 and over. This is a known trend which clearly reflects that this generation did not grow up with digital technologies and is generally less exposed or rather uninterested in using conversational agents. However, these two studies, covering the year 2024, do not include individuals under 18 years old. Yet this population, even if absent from the statistics, represents a segment particularly exposed to digital technologies especially in educational contexts. Moreover, in the case of adolescents who are still in a phase of brain development the impact of cognitive delegation on memory could be more pronounced, which reinforces the interest in examining age as a moderating variable of the cognitive effects related to the use of conversational agents.

Moreover, M., P. V. S. & Kryvinska (2024) show that trust in chatbots influences the willingness to use, expressed by young adults, especially those aged 21 to 26 for whom these tools are seen as compatible with their information search habits. Trust is at the core of repeated use and engagement (P. V. S. & Kryvinska, 2024). Finally, Menon and Shilpa (2023) argue that older users rely more on their judgment and are less receptive to perceived ease or interactivity. Due to their greater experience, these profiles tend to use other cognitive strategies which could make the effects of reliance observed in young people less significant.

- **Hypothesis (H4):** Age moderates the relationship between reliance on conversational AI and non-assisted memory so that this effect is stronger among young users for whom cognitive automation through ChatGPT tends to be more natural and more frequent.

The education level

Education level plays a key role in the development of higher-order cognitive skills, particularly critical thinking. As Walter (2024) points out, a solid educational background provides not only the technical skills needed to use AI tools effectively, but also the reflective foundation necessary to assess their benefits, limitations, and the ethical issues they raise. In this sense, education serves as a protective factor against excessive cognitive delegation by promoting a conscious and reasoned appropriation of digital technologies.

However, the link between educational attainment and cognitive autonomy cannot be considered absolute. Recent studies nuance this relationship by showing that even highly educated individuals may adopt an over-reliant stance toward AI, to the detriment of their independent thinking skills. For example, Salim Jr et al. (2023) observe that among qualified professionals, prolonged use of AI-based decision-support tools can inhibit the activation of critical reasoning, leading to functional dependency and reduced intellectual vigilance. Similarly, Bai et al. (2023) note that immediate access to AI-generated answers may short-circuit processes of analysis, evaluation, or judgment by limiting the cognitive effort required for deep understanding.

This phenomenon is particularly concerning in educational contexts, where users are still in the process of developing their cognitive abilities. Among young adults, who are often still undergoing academic training, reliance on conversational agents may hinder the development of critical skills that are normally reinforced through educational experience, thereby limiting the ability to process and retain information independently. Prolonged exposure to interfaces such as ChatGPT, without critical distance, may constrain the maturation of reflective abilities, amplifying the negative effects of reliance on internal memory and information retention (Salim Jr et al., 2023).

This suggests that education level does not automatically protect against the cognitive risks associated with intensive AI use, particularly among younger generations, who are still intellectually developing and especially prone to adopting automated uses of such technologies.

- **Hypothesis (H5):** Education level moderates the relationship between reliance on conversational AI and non-assisted memory, such that a higher level of education mitigates the negative effects of reliance on information retention.

- **Hypothesis bis (H5b):** Education level moderates the relationship between reliance on conversational AI and non-assisted memory: although a higher level of education may reduce the negative effects of reliance, this protective effect weakens among young adults still in training, who are more likely to adopt automated uses of AI.

2.2.5. Summary of the proposed model

Variables:

- Independent variable : Reliance on conversational AI
- Dependent variable: Non-assisted memory
- Mediating : Trust in Conversational AI and the information provided by the chatbot
  Moderators :
  - Complexity of the researched information
  - Age of the individual
  - Level of education

Hypotheses:

- **Hypothesis (H1).** A higher reliance on conversational AI (measured by usage frequency and perceived convenience), is associated with a decrease in the non-assisted memory for product-related information.

- **Hypothesis (H2).** Trust in conversational AI and in the information it provides mediates the relationship between reliance on AI and unaided memory, such that a high level of trust amplifies the reduction in unaided memory associated with chatbot use.

- **Hypothesis (H3):** The complexity of the information sought moderates the relationship between reliance on conversational AI and unaided memory, such that more complex information leads to increased reliance on AI and, consequently, to a more pronounced reduction in unaided memory.

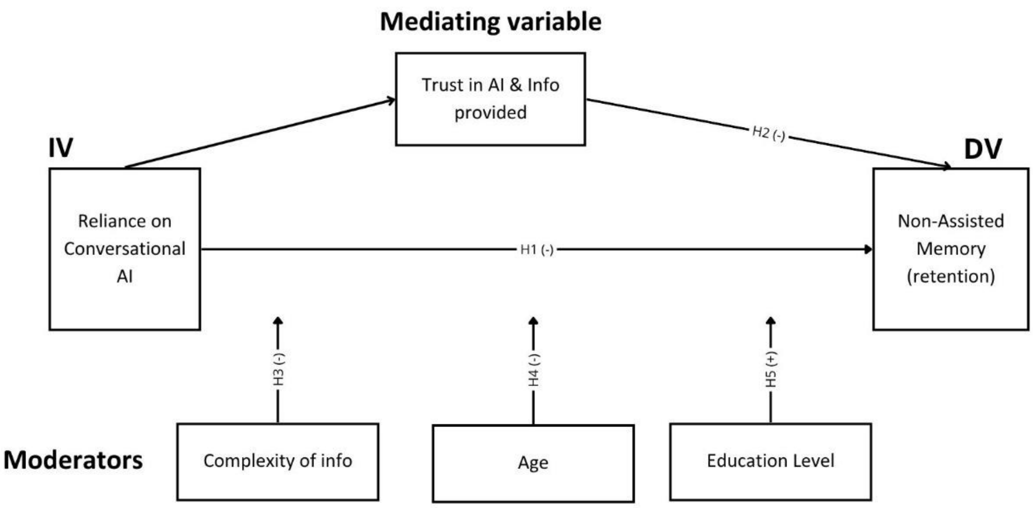
- **Hypothesis (H4):** Age moderates the relationship between reliance on conversational AI and non-assisted memory so that this effect is stronger among young users for whom cognitive automation through ChatGPT tends to be more natural and more frequent.

- **Hypothesis (H5):** Education level moderates the relationship between reliance on conversational AI and non-assisted memory, such that a higher level of education mitigates the negative effects of reliance on information retention.

- **Hypothesis bis (H5b):** Education level moderates the relationship between reliance on conversational AI and non-assisted memory: although a higher level of education may reduce the negative effects of reliance, this protective effect weakens among young adults still in training, who are more likely to adopt automated uses of AI.

Conceptual model:

Figure 1 : conceptual model



III. Research design

3.1. Methodology

3.1.1. Research approach

This study relies on a quantitative approach, based on the implementation of a structured questionnaire with a small experimental component. This decision follows a deductive approach, drawing on the theoretical contributions of recent literature to formulate hypotheses for empirical testing. If a qualitative exploratory approach could be envisioned, for instance, due to the relatively understudied nature of the relationship between conversational AI and memory, the explanatory nature of this research, which aims to quantify the impact of one variable (using AI to gather product information) on another (the unaided memory associated with this information), justifies the use of a quantitative method.

As reminded by Malhotra & Birks (2007), conclusive quantitative research allows for the testing of precise hypotheses through a structured methodology, representative samples, and data analysis based on statistical tools. Moreover, unlike previous research on digital memory (such as the Google effect, digital amnesia, or cognitive offloading), which mainly relied on experimentation, this study favors a questionnaire-based survey due to time and resource constraints, while maintaining an explanatory objective. Given the novelty of the topic, this study represents a first empirical step toward better understanding these cognitive effects in a consumption context.

Although this study aims to explore the potential link between the use of conversational artificial intelligence (ChatGPT) and consumers' unassisted memory, it does not in itself constitute causal research. Indeed, as Malhotra & Birks (2007) also point out, causal research typically requires formal experimentation in a controlled setting, where the independent variable is manipulated and all other elements are strictly controlled. However, in this study, no strict control of the environment is implemented, and the experimental component is limited to a brief segment embedded within the data collection tool. Therefore, the statistical analyses used in this study can only indirectly infer a possible causality.

This research, unlike many others on artificial intelligence and conversational agents, is not based on a theoretical framework such as the Technology Acceptance Model (TAM) (Davis, 1989) or the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003). While these models are useful for examining usage motivations or technology acceptance, they are not well suited to the specific focus of this study, which looks at the impact of using ChatGPT on unassisted brand-related memory. The goal is not to predict the intention to use AI, but rather to analyze its cognitive impact. Therefore, a standard theoretical model of technology acceptance would not have provided a sufficiently appropriate structure for this research.

3.1.2. Data collection

The data collection instrument chosen for this research is an online questionnaire, which is in line with the quantitative approach of the study. It is also available in Appendix X. This decision is motivated by the multiple strengths of this method: online surveys are currently very common in many fields, including marketing, as they offer fast, flexible and low-cost data collection (Malhotra & Birks, 2007). One of the advantages of closed questions is that they are easier and quicker for participants to process, which may potentially enhance their response rate. This format appears particularly well suited to explore the initial effects of using AI tools on brand-related memory, while reaching a large and diverse sample.

Nevertheless, this option also presents constraints, notably the lack of control over the administration context, which is especially relevant in the case of the short experiment integrated into the questionnaire. This factor may introduce uncontrolled biases or contextual effects, which will be discussed in more detail in the section dedicated to the questionnaire design. Finally, given that the concept of digital amnesia associated with conversational AIs is still in its early stages, the use of a survey makes it possible to collect a variety of viewpoints and identify general trends, thus laying the groundwork for more in-depth experimental research in the future.

However, considering that the questionnaire is mostly based on closed and declarative questions, a brief experiment was incorporated into the process to more directly assess a potential effect on unassisted memory. Indeed, during the development of the survey, it was taken into account that asking participants a subjective question, for instance, soliciting their own judgment on how well they remember the information they had searched, could lead to biased responses, particularly due to an overestimation of their ability to retain information. As a result, a simple self-reported perception did not seem sufficient to accurately capture the real impact of AI use on memory. This is why the inclusion of a short experimental component in the questionnaire aims to reveal a potential effect on memory, while remaining compatible with the logistical constraints of the online survey.

This choice also align well with the methodological approaches implemented in several previous studies on digital amnesia, the Google effect or cognitive offloading, which are primarily based on experimental protocols. The specific choices related to this experiment are detailed in the following section, dedicated to the structure of the questionnaire.

3.1.3. Survey construction

The choice of a structured questionnaire is based on various practical and methodological considerations. First, ChatGPT was selected as the integrated experimental tool for several reasons. It was essential to use an AI-based chatbot that is not limited to predefined scenarios and does not focus solely on widely recognized mainstream products. ChatGPT met these criteria while offering another advantage: its high popularity and accessibility, which could potentially increase the number of responses collected. In contrast, asking participants to use an unfamiliar chatbot or navigate an external website could have led to early dropouts, thereby jeopardizing the participation rate.

The questionnaire is structured in several parts: it begins with the short experiment, then continues with questions related to the different variables studied, then addresses the variable concerning unassisted memory, including questions about the experiment carried out at the beginning and ends with demographic questions, corresponding to two of the model's moderators.

Therefore, the survey starts directly with the instructions related to this experiment. Participants are invited to carry out two comparative product evaluations using ChatGPT. More precisely, they are asked to assess their preference between two products based on certain criteria, which leads them to consult and compare the characteristics of each option.

The choice of these products was not made randomly: the objective was to select brands and products that were less known for most people, to diminish participants' pre-existing knowledge and thus to increase the validity of the memory evaluation.

However, this choice involves potential limitations. Although the selected products are common, they are likely to appear more appealing or familiar to younger generations and therefore, may seem less relevant or interesting to an older audience. Thus, it is possible that the latter were less engaged in the task, which could have influenced both their involvement in the research and their ability to retain information. This observation may also further support the relevance of having included age as a moderating variable, as this factor could influence both interest in the products and memory performance. Nevertheless, it is important to note that the perceived relevance of the products by each individual was not an aspect directly controlled in this study.

After completing their research, participants received a crucial instruction: they either had to close the ChatGPT conversation window or to delete it from their history. This directive aims to reduce biases related to the lack of control over the environment. Indeed, in a digital setting, participants might be tempted to revisit their conversations in order to correctly answer the open-ended questions regarding the selected information. The goal of this measure is therefore to preserve, as much as possible, the authenticity of the response related to unassisted memory. However, despite this precaution, the lack of control over the environment remains a significant limitation. Factors such as multitasking or external distractions may also affect memory performance.

The development of the questionnaire was also carried out in line with the research objectives. Although this study does not directly measure long-term memory due to its non-longitudinal nature, it was important to include a latency period between the research phase and the retrieval of information, to observe a possible effect on information retention. Then, following the first experimental phase, participants are asked to answer several series of closed-ended questions concerning the study's variables (AI usage, trust, perceived complexity, etc.). At the end of the questionnaire, they are invited to revisit the information they were asked to look for, by responding to open-ended questions to assess what they remembered.

The initial idea was to introduce a brief intellectual activity (such as a mini-game or a sudoku) to induce distraction and simulate a delay. However, this approach was abandoned for practical reasons: for instance, it would have lengthened the questionnaire and potentially discouraged participants, thereby increasing the risk of dropout. Simply placing the measurement questions between the research phase and the memory-related questions was therefore intended as a methodological compromise.

At the end of the survey, participants were asked to share the information they remembered in an open-ended question. To ensure that the responses are not influenced by some pre-existing knowledge, an additional question asked whether they already knew the answer before conducting the research. Finally, on the page following the open-ended questions, the same questions are presented again in a multiple-choice format. This allows the data to be combined with the open responses to facilitate statistical analysis, while acknowledging that the multiple-choice format may support recognition of information and thus aid memory.

An essential aspect in the development of this questionnaire is that participants were not totally aware of the true subject of the study, concerning the potential impact on memory, since it was not explicitly mentioned to participants. The questionnaire was simply presented as a survey on the use of ChatGPT for product information searches. This approach aimed to prevent participants from adjusting their behaviour, for instance by making a special effort to memorize or by cheating (such as taking notes or deliberately keeping the conversation open). This intention bias could have distorted the actual assessment of unassisted memory.

3.1.4. Sampling method

For this study, a non-probability sampling strategy was chosen, with a focus on the convenience sampling technique. That is, participants were selected based on their accessibility and availability, meaning that they were "in the right place at the right time" (Malhotra & Birks, 2017). In this sense, the questionnaire was mainly distributed through several social media platforms.

Convenience sampling offers several practical advantages, in terms of time savings, low costs and ease of access to respondents. This technique is also more easily implemented in the context of an online survey, which is quicker to complete and more convenient for participants. It may potentially allow for reaching a wide range of respondents, but without any guarantee or control over the diversity achieved.

Nevertheless, this technique also has some drawbacks. Indeed, since participants are recruited based on their availability and willingness, meaning that certain profiles could therefore be underrepresented, possibly affecting the representativeness of the sample. This could represent a serious limitation for this research, especially if certain participant characteristics are essential for analysing moderating effects.

Although this method has certain limitations, it remains suitable for the objectives of this research, which aims to shed light on relatively understudied cognitive mechanisms in the field of conversational AI.

3.1.5. Survey conduction

The questionnaire was designed and delivered through the LimeSurvey platform, which is GDPR compliant (General Data Protection Regulation), ensuring the protection, security and anonymity of the collected data. On average, the time required to complete the questionnaire ranged from 10 to 15 minutes, especially for those who were less familiar with the ChatGPT tool. Even though answering the questions took only about 5 to 7 minutes, the time spent searching for and reading information on ChatGPT also had to be considered.

Before being published online, the questionnaire was pre-tested by three individuals from different age groups to ensure that the questions were clear, to identify any spelling and possible typos, to evaluate the structure of the questionnaire and to test the research task using ChatGPT, as well as to measure the total time required to complete it. Based on their feedback, a few minor adjustments were made.

As previously mentioned, the distribution of the questionnaire was mainly carried out through various social media platforms and by word of mouth. It remained accessible for nearly a month. However, due to the necessity to gather a minimum of 100 participants, the questionnaire was also shared in Facebook groups dedicated to student survey exchange, as well as on the websites SurveyCircle and SurveySwap, which operate on a reciprocity system (completing a questionnaire to earn points, in order to make one's own survey more visible in a ranking and increase the chances of receiving more responses). These two platforms generated approximately 25 responses. A disadvantage of this distribution method is that it may lead to an overrepresentation of young adults, generally students, which could limit the diversity in the sample in terms of age and education level, both of which are moderating variables in this study.

3.1.6. Data preparation and cleaning

A total of 159 responses were collected through the online questionnaire. Among these, 108 were complete, while 51 were not. For the statistical analyses, only the complete responses were taken into account. Subsequently, a light data cleaning was performed to ensure the accuracy of the results, particularly in relation to the dependent variable associated with unassisted memory.

According to the experimental protocol, participants were instructed to either close the ChatGPT page or delete the conversation from their history after completing their research. This directive aimed to prevent them from consulting the AI-generated responses, in order to preserve the integrity of the unassisted memory evaluation. Four individuals reported not having followed this instruction and were therefore excluded from the analysis. It is worth noting that two of them also provided clearly incorrect answers in the open-ended questions (such as mentioning products that were never referenced in the content generated by ChatGPT), further justifying their exclusion.

Two other responses were also excluded. In one case, the entire questionnaire had been completed automatically, with uniform answers to all questions and no responses provided for the open-ended items, indicating a lack of genuine engagement, likely motivated by the points-based system of platforms such as SurveyCircle or SurveySwap. In the other case, the participant mentioned a product that was not included in the generated content, which likely suggests a misunderstanding of the instruction.

Therefore, the final sample retained for analysis includes 102 participants.

Then, participants who reported already knowing the answer to certain questions before conducting their research were not systematically excluded. A brief analysis of their open-ended responses revealed that, despite their statement, they did not necessarily recall the searched elements accurately or provided only approximate answers. Thus, it still seemed relevant to include them, as their performance did not appear to reflect prior memorization that could significantly distort the results.

3.2. Scales and measures

The questionnaire used in this study consisted primarily of multiple-choice closed-ended questions, with the addition of two open-ended questions. Several rating scales were employed to measure the key variables of the study, all drawn from Bruner II's *Marketing Scales Handbook* (2009): *A Compilation of Multi-Item Measures for Consumer Behavior & Advertising Research*.

Five-point Likert scales were used for most of the variables since it is a common method, particularly in marketing research. The Likert scale is a non-comparative, itemized rating scale, with each statement being evaluated independently of the others. Respondents are asked to indicate their level of agreement or disagreement with a series of statements to better assess them (Malhotra et al., 2017).

The decision to favour the 5-point scale over a 7-point scale, despite the variety of options found in the literature, is justified by the assumption that the 5-point scale already allows respondents to sufficiently nuance their answers.

Moreover, the Likert scale represents a valuable methodological asset, as it is relatively simple to construct, easy to administer, and generally well received by respondents, making it particularly well suited for self-administered online questionnaires (Malhotra et al., 2017). However, this scale also has limitations, such as a potentially longer response time compared to other scales, since participants must, for example, read each item carefully and reflect before answering. This drawback was considered acceptable in the context of this research, as the quality of the measurement was worth the trade-off.

For certain variables, various scales were sometimes used, primarily based on what is suggested in the literature. The selected scales were chosen for their suitability in providing a relevant and reliable measurement of the variables under study, while aiming to remain consistent with how previous research has addressed it in the field.

Nevertheless, a peer-reviewed scale recently developed by Tao, Zhang, and Liu (2024), which is particularly well suited to the issue addressed in this research, focusing on individuals' use of AI-based creativity tools during creative tasks, had not yet been identified at the time of constructing the theoretical framework. Its integration into future work could allow for a more precise and rigorous measurement of the mechanisms of cognitive delegation to AI-based tools.

3.2.1. Perceived complexity of the information

The Easiness Scale from Tybout et al. (2005) was used and modified to measure perceived information complexity. The scale originally included four semantic differential items, but it was reworded into statements on a 5-point Likert scale to match the overall format of the questionnaire. The original wording of the scale was preserved (e.g. "easy", "simple). However, the items were reworded as declarative statements to fit the Likert scale format. Since the scale was measuring perceived easiness, the scores were reverse-coded to represent perceived complexity, consistent with the conceptual definition used in the model.

3.2.2. Reliance on ChatGPT

Reliance was measured using three complementary measures. First, a shorter version of the Easiness Scale by Tybout et al. (2005) (3 items) measured how easy the participants perceived ChatGPT to be when searching for information as ease of use is often linked to greater reliance. The scale was converted to a 5-point Likert format, to align with the format of the survey. Only three items were retained based on the fact that one of the original items was deemed to be redundant to another item.

Second, the Internet Usage (Convenience Motivation) scale (Ko et al., 2005) was used to represent a motivational dimension of reliance, which is the tendency to prefer tools perceived as convenient and easy to use. The original items were slightly modified by replacing the generic term ''it'' with ''ChatGPT'' to better fit the context. This scale has demonstrated good reliability and was part of a validated factor structure in the original study.

Third, the Loyalty (Action) scale (Harris and Goode, 2004) was used to capture the intention of participants to keep on using ChatGPT above other sources. This behavioral aspect of reliance reflects longer-term preferences. All items were rated using 5-point Likert scales. The scale displayed satisfactory reliability and showed convergent and discriminant validity during its original development (Harris and Goode, 2004).

3.2.3. Trust in AI and the information provided

The Attitude Toward the Website (Trust) scale (Bart et al., 2005) was used twice : first to measure trust in AI-generated content in a general sense and secondly, to measure the trust in the responses provided by ChatGPT in general. In both cases, the expression "this site" was replaced accordingly. These two uses represent how the mediating variable trust was measured in this study. The scale was shown to have strong reliability and strong convergent and discriminant validity in the original validation.

3.2.4. Self-confidence in judgment

Despite not being directly part of the conceptual model, to enrich the descriptive profiling, the Self-Confidence (Judgment Correctness) scale from Urbany et al. (1997) was included. Once again, the original semantic differential scale was modified to fit the point Likert items while maintaining the original terms. This measure provides insight into the participants' confidence in the correctness of their judgments, which could be especially relevant when reflecting on what they think they memorized. The scale has reported strong reliability in studies, especially Urbany et al. (1997).

IV. Results

4.1. Reliability of the scales[1]

Although the scales used in this study were recovered from existing literature, some were adapted or modified, for instance to better fit the context. Therefore, it was needed to reevaluate their internal reliability using Cronbach's alpha, in addition to the original alphas reported by the authors. It is important to take the reliability of a scale into account since it indicates how consistent and stable it is in its measurements. A comparative table of all the reliability coefficients is presented below.

The perceived convenience, which is one of the components of the variable ''reliance on AI'', was measured using three items on a 5 points Likert-type scale. The internal consistency analysis shows acceptable reliability for this subscale (Cronbach's alpha = 0.72), allowing to ultimately form an overall measure of convenience perception with these items.

Then, another component of this represents the perceived ease of use of the tool, measured using three items. The internal consistency analysis indicates excellent reliability for this subscale, with a Cronbach's alpha of 0.92. All items contribute strongly to the overall consistency, justifying their use.

[1] *See in Appendix 2*

The willingness to continue using the tool compared to other sources of information, which is captured in this study as the loyalty, was measured using four items. The internal reliability analysis reveals very good consistency (Cronbach's alpha = 0.90), which also allows these items to be used for this component.

The component "trust in the responses provided by artificial intelligence" was measured using three items on a Likert-type scale. The internal reliability analysis indicated excellent internal consistency of the scale, with a Cronbach's alpha of 0.80.

The component "trust in the responses provided by ChatGPT" was measured using three items assessed on a Likert-type scale. The internal consistency analysis shows very good reliability of the scale, with a Cronbach's alpha of 0.81.

The moderating variable "information complexity" was measured using four items on a Likert-type scale. The internal reliability analysis showed moderate consistency (Cronbach's alpha = 0.72), still allowing the items to be combined into a single score to represent the perceived level of complexity.

A complementary scale was also used to measure self-judgment, which represent the degree of self-confidence participants felt regarding their ability to retain the information they searched. This measure is based on three semantic differentials. The internal reliability analysis revealed great consistency of the scale (Cronbach's alpha = 0.92), allowing this score to be interpreted as a reliable indicator of confidence in one's own memory.

Figure 2 : reliability of the scales

Scale name	Variable measured	Cronbach's α (customized scale)	Cronbach's α (original scale)
Internet Usage (Convenience Motivation)	Reliance on AI (perceived convenience)	0.72	0.65 (Ko, Cho, and Roberts 2005)
Easiness	Reliance on AI (ease of use)	0.92	< 0.90
Attitude Toward the Website (Trust)	Trust in AI responses	0.8	0.91 (Bart et al. 2005)
Attitude Toward the Website (Trust)	Trust in ChatGPT responses	0.81	0.91 (Bart et al. 2005)
Easiness	Perceived complexity of the information	0.72	< 0.90
Self-Confidence (Judgment Correctness)	Self confidence in memory retention	0.92	- 0.93 & 0.94 (Urbany et al., 1997) - 0.85 (Zhang and Budda, 1999) - 0.95 (Keller et al., 2002)

Loyalty (Action)	Loyalty (continue of use Vs. Other sources)	0.9	0.74 & 0.78 (Harris and Goode, 2004)

4.2. Validity of the scales[2]

Before interpreting the relationships between variables, it is essential to ensure that the scales used accurately measure the intended concepts. In this study, certain items from distinct scales were combined to construct composite variables, making it necessary to assess construct validity to ensure the theoretical relevance of these groupings. Therefore, confirmatory factor analyses were conducted via the JASP interface.

After conducting a CFA on the ten items that were supposed to measure the reliance on conversation AI, including perceived convenience, ease of use and usage loyalty, the latter was removed from components of this variable. Indeed, the p-value was significant, indicating a poor model fit, the CFI (0.452) and the RMSEA (0.313) were quite far from their threshold and the factor loadings were also very low. This suggested that this dimension did not integrate well into the overall reliance factor.

However, after conducting the CFA on only the six remaining items measuring the reliance on AI, without the loyalty dimension, the scale became more relevant and valid. In this case, all the factor loadings were strong, the p-value (<0.001) indicated a very good fit, the CFI (0.891) and the RMSEA (0.196) were closed to their acceptable threshold. This trade-off was therefore adopted to improve the quality of the measurement and the adjusted scale was retained for the subsequent analyses.

Since usage loyalty was removed from the overall "reliance on conversational AI" variable for scale validity reasons, it was tested separately. The p-value of 0.524 is non-significant, indicating a good fit between the model and the data. The CFI and the RMSEA (0) both indicated a good fit. These results indicate that the usage loyalty has a valid and coherent factorial structure, when separated from the other components of the reliance variable.

A confirmatory factor analysis (CFA) was conducted on the six items measuring participants' trust in responses provided by artificial intelligence in general (3 items) and by ChatGPT specifically (3 items), to validate a unidimensional structure for the variable "trust." The chi-square test is significant ($p < .001$), indicating an unsatisfactory model fit. The CFI is 0.828, below the acceptable threshold of 0.90, and the RMSEA is high ($0.256 > 0.10$), confirming a poor overall fit.

A CFA was conducted on the six items measuring participants' trust in responses provided by artificial intelligence in general (3 items) and by ChatGPT specifically (3 items), in order to validate a unidimensional structure for the variable "trust." The chi-square test is significant ($p < .001$), indicating an unsatisfactory model fit. The CFI is 0.828 was below the acceptable threshold of 0.90 and the RMSEA was rather high ($0.256 > 0.10$), confirming a poor overall fit. Despite these results, all factor loadings are significant, and each item contributes consistently to the measured dimension. The scale was therefore retained, taking into account its theoretical validity and its role within the model. Furthermore, since this variable is used here as a potential mediator and not tested directly in a causal manner, some flexibility is allowed regarding the model fit quality.

[2] *See in Appendix 3*

The CFA conducted on the three items measuring self-judgment did not give a p-value in JASP, but the other elements indicate a good model fit. The CFI is 1, reflecting a perfect fit (≥ 0.90) and the RMSEA is 0, which is optimal (expected value < 0.10). All factor loadings are high and significant. Thus, this scale was retained for the analyses.

The CFA conducted on the four items measuring the perceived complexity of ChatGPT's response indicated an unsatisfactory p-value score of 0.0004 (<0.05), which can mean that the factor structure might not be a good fit for the data. The CFI is 0.905, which meets the acceptable threshold (≥ 0.90) and all factor loadings are significant. The RMSEA is rather high (0.209 > 0.10), indicating limited model fit. Despite these limitations, the scale was retained due to the consistent contribution of each item, the quality of the factor loadings and the theoretical grounding of the measured dimension.

Figure 3 : validity of the scales

Variable	Items	p-value (χ^2)	CFI	RMSEA	Factor Loadings	Conclusion
Reliance (10 items incl. loyalty)	10	< 0.001	0.452	0.313	Low, some non-significant	Poor fit – Loyalty removed
Reliance (6 items excl. loyalty)	6	< 0.001	0.891	0.196	Strong, all significant	Acceptable – Scale retained
Loyalty (separate CFA)	4	0.524	1.000	0.000	High, all significant	Excellent fit – Separate valid construct
Trust (AI + ChatGPT)	6	< 0.001	0.828	0.256	All significant	Poor fit – Retained due to theoretical relevance
Self-judgment	3	(No p-value)	1.000	0.000	High, all significant	Excellent fit – Scale retained

Perceived complexity	4	0.004	0.905	0.209	All significant	Limited fit – Retained for theoretical consistency

4.3. Descriptive analysis of the sample[3]

4.3.1. Sociodemographic characteristics

The sample is composed of 102 participants. Regarding the age distribution, the respondents are mostly young adults. Indeed, more than half of the participants (55.9%) are between 18 and 24 years old and a quarter (25.5%) are between 25 and 34 years old. Older individuals are more marginal in number: 7.8% of respondents are between 35 and 44 years old, 5.9% are between 45 and 54 years old and only 1% are over 55 years old, while only one person (1% of the sample) is under 18 years old.

Regarding the level of education, 44.1% of the participants have a Bachelor's degree, 38.2% a Master's degree and 14.7% a secondary school diploma. Very few respondents (2.9%) indicated another level of education, such as a PhD or a double degree. No respondent declared having no diploma.

4.3.2. Use and reliance on conversational Artificial Intelligence

The evaluation of dependence on conversational AI was carried out through several aspects: perceived convenience, ease of use and regular use of ChatGPT to obtain information about products or brands. A very large majority of participants (97.1%) find the tool easy and intuitive to use. Additionally, 95.1% consider its use to be practical.

The use of ChatGPT for searching information about brands or products was measured using a scale ranging from "never" to "very often." The results are fairly balanced: 29.4% of respondents never use the tool, 31.4% use it rarely, around 13% sometimes, 12.7% often and 13.7% very often. For the purposes of statistical analyses, this variable was also recoded into a binary form, contrasting infrequent users on one side and frequent users on the other.

Taking all these dimensions into account, 94.1% of participants could potentially be considered dependent on conversational AI and ChatGPT, based on the criteria established in the study. Only 5.9% show sporadic or limited use of the tool.

4.3.3. Trust in AI and ChatGPT responses

[3] *See in Appendix 4*

Participants' trust in the responses provided by artificial intelligence was assessed in two ways. On the one hand they were asked to what extent they trusted information produced by AI in general. On the other hand a question specifically targeted their trust in the responses provided by ChatGPT. The data show a strong similarity between these two aspects, with 81.4% of respondents stating they trust ChatGPT's responses and 81.3% also expressing trust in artificial intelligence responses in general.

4.3.4. Perceived information complexity

The evaluation of the complexity of the information provided by ChatGPT was based on participants' subjective assessment. An overwhelming majority (98%) found the response to be clear, while only 2% considered it complex.

4.3.5. Self-judgment of correctness and memory retention

In addition to more objective assessments of memory, participants were asked to self-evaluate their ability to retain the information communicated by ChatGPT. This self-assessment of judgment shows that 70.6% of participants reported having correctly retained the information. Although this variable is not directly included in the conceptual model, it provides additional insight into individual perceptions of cognitive performance.

Memory retention was assessed using two multiple-choice questions related to the information search that participants were asked to perform at the beginning of the questionnaire, aiming to measure their ability to recall information obtained via ChatGPT without external help. The results show that 73.5% of participants failed to answer one or both questions correctly, thus demonstrating limited information retention, while only 26.5% of participants answered correctly.

The number of participants who believed they did retain the required information compared to the ones who did provide the right answer highlights a marked discrepancy between perceived memory ability and actual performance.

4.3.6. Loyalty

Regarding loyalty to the tool, 40.2% of respondents stated that they would reuse ChatGPT for this type of task rather than another source of information.

It is worth noting that, initially, usage loyalty was intended to be included in the overall assessment of trust in conversational artificial intelligence. However, this component was removed to improve the validity of the scale. Nevertheless, it remains relevant, as it reflects a willingness to reuse ChatGPT for this type of research, especially in comparison to other sources of information.

4.4. Statistical analysis

4.4.1. Chi-square tests

H1 – Reliance on AI and Non-Assisted Memory

Hypothesis H1 suggested that the more frequent and convenient the use of conversational artificial intelligence, the lower the non-assisted memory related to brand information.

To examine this correlation, a Chi-square test was conducted, since it was adapted to the data collected for this research. Indeed, both variables are nominal and dichotomous in nature: AI usage (coded 0 for low, 1 for high) and non-assisted memory (coded 0 for low, 1 for high). The application of the Chi-square test thus allows for examining whether the distribution of memory levels varies significantly according to the degree of AI usage, which aligns with the objective of this exploratory research.

Before interpreting the results, it is important to ensure that the conditions for applying the test are met. Although the contingency table is of type 2×2 and the assumption of independence of observations is respected, one of the cells has a frequency count of less than 5, which challenges the statistical validity of the test in question.

Nevertheless, the results of the Chi-square test yield a value of $\chi^2(1)=0.315$ with a p-value of 0.575. Given that the p-value is well above the conventional threshold of 0.05, it indicates that no significant association between the level of reliance on AI and non-assisted memory was found in this case.

Therefore, hypothesis H1 is not confirmed at this stage. However, caution is warranted when interpreting this conclusion, given the low frequencies in certain categories, which limit the power of the test and the robustness of the possible inferences.

Figure 4 : Chi-square – Reliance on AI & Non-assisted memory

Chi-Squared Tests

	Value	df	p
X^2	0.315	1	0.575
N	102		

4.4.2. Mediation Analysis[4]

In order to test the hypothesis of a potential mediating effect of trust in AI in the relationship between reliance on AI and non-assisted memory, a mediation analysis was conducted using the Mediation Analysis module in JASP. The mediator and dependent variables, initially binary, were temporarily

[4] *See in Appendix 6*

recast as “Scale” format to allow their inclusion in the SEM model, in accordance with the options provided by JASP. Although this treatment is a simplification, it enables an exploratory estimation of both direct and indirect effects.

In this study, although the variables were initially nominal, they could be treated as continuous (scale-type) variables in JASP, since they were binary (coded as 0/1). This approach can be accepted for exploratory mediation models.

The model indicates that the direct impact of AI use on non-assisted memory is not significant (β = 0.103, p = 0.583, 95% CI = [–0.265; 0.472]). Furthermore, the indirect effect through trust in AI is very weak and not significant (β = 0.0009, p = 0.976). The total effect, which includes both direct and indirect effects, also shows no significance (β = 0.104, p = 0.574, 95% CI = [–0.259; 0.467]).

According to the traditional significance threshold set at $p < 0.05$, none of the effects are considered significant. All 95% confidence intervals include the value zero, which highlights the absence of a strong effect, whether direct or mediated.

These findings fall within the context of a “no-effect non mediation” (Zhao, Lynch & Chen, 2010), meaning a pattern in which neither the direct effect nor the indirect effect is detected.

In conclusion, the study provides no statistical evidence of a mediating role of trust between AI use and non-assisted memory in this exploratory model.

4.4.3. Moderation analysis[5]

H3 – Complexity of Information

Hypothesis H3 proposed that the perceived complexity of the information would moderate the relationship between reliance on AI and non-assisted memory, such that information perceived as more complex would lead to stronger reliance on AI, thereby resulting in a more pronounced reduction in non-assisted memory.

To explore this moderating effect, a Chi-square test was conducted separately for each level of perceived complexity, by filtering the moderator variable in JASP (0 = low complexity; 1 = high complexity) and generating 2×2 contingency tables for each subgroup in order to test the dependency between reliance on AI and memory performance.

However, only two participants were classified under the “high perceived complexity” condition, which made it impossible to perform a reliable statistical analysis on this subgroup (insufficient counts in the contingency table cells). As a result, hypothesis H3 could not be empirically tested, leaving the question of a potential moderating effect of perceived information complexity unanswered. This limitation will be addressed more specifically in the Limitations section of this thesis.

[5] *See in Appendix 7*

H4 – Age

Hypothesis H4 suggested that age moderates the relationship between reliance on conversational AI and non-assisted memory, with this effect expected to be stronger among younger users, for whom cognitive automation through tools like ChatGPT would be more natural and frequent.

To explore this hypothesis, a moderation analysis was conducted using Chi-square tests, performed separately within two age groups. The age variable was recoded into a binary variable (1 = subjects under 34 years old; 2 = subjects aged 35 and above).

Within each group, the association between reliance on AI and non-assisted memory was examined using a 2×2 contingency table in JASP. In the first group (≤ 34 years old, N = 84), the link between reliance and memory was found to be non-significant ($\chi^2 = 0.026$, $p = 0.871$). In the second group (> 35 years old, N = 18), the Chi-square test also yielded a non-significant result ($\chi^2 = 0.450$, $p = 0.502$).

The hypothesis predicted a stronger effect in the younger group; however, this assumption is not supported by the data. Moreover, the small sample size of the older group limits the statistical power and interpretative scope of the results. Therefore, Hypothesis H4 is not confirmed in this study.

Figure 5 : Chi-square results by age group

Age group	N	χ2	df	p	Significant (<0.05)
≤ 34 years old (Group 1)	84	0.026	1	0.871	No
> 35 years old (Group 2)	18	0.450	1	0.502	No

***Note**: The theoretical threshold for significance is p less than 0.05. Neither group reached this threshold.*

H5 – Education level

Hypothesis H5 stated that the level of education moderates the relationship between reliance on conversational artificial intelligence and non-assisted memory, with a higher level of education reducing the negative effects of reliance on retention.

To test this hypothesis, an exploratory moderation analysis was conducted using Chi-square tests, performed separately for two educational groups. The education level variable was recoded into two categories to ensure the validity of the statistical test (Group 1 = no diploma, secondary education, bachelor's degree; Group 2 = master's degree, PhD, or other higher education degree).

In the lower education group[6] (N = 45), the Chi-square test did not reveal a significant relationship between reliance on AI and non-assisted memory ($\chi^2 = 0.761$, $p = 0.383$). This relationship was also not significant in the higher education group (N = 57) ($\chi^2 = 0.004$, $p = 0.951$).

Therefore, the data from this study do not support Hypothesis H5. No moderating effect of education level was observed on the relationship between AI use and memory.

Figure 6 : Chi-square results by education group

Education group	N	χ2	df	p	Significant (<0.05)
Lower education (Group 1)	45	0.761	1	0.383	No
Higher education (Group 2)	57	0.004	1	0.951	No

Note*: The theoretical threshold for significance is p less than 0.05. Neither group reached this threshold*

H5b – Complementary hypothesis on the interaction between education and age

Hypothesis H5b proposed that the level of education moderates the relationship between the use of conversational AI and non-assisted memory. However, this supposed beneficial effect of a high level of education might be less pronounced among young adults in training, due to their greater tendency to adopt automated uses of AI.

This hypothesis therefore assumed a joint interaction between age and education level regarding the effect of AI reliance.

However, the findings of the previous hypotheses showed no significant moderating influence of age (H4) or education level (H5) on the relationship between reliance and memory.

Therefore, the secondary hypothesis H5b will not be examined in this study, as the empirical and statistical conditions required to test a moderated two-factor interaction are not met.

4.5. Brief insights from the open-ended questions

A brief analysis was carried out based on the open-ended responses to the question about the searched participants needed to conduct at the beginning of the survey. This step was not designed as a rigorous qualitative study, as the open-ended questions were not intended for systematic qualitative

[6] *The terms "lower education level" and "higher education level" are used solely for statistical purposes, with no normative intent or value judgment. This is simply a technical grouping used to distinguish between two sets of educational qualifications for the purposes of analysis.*

coding or categorization. The purpose was to informally explore what participants could spontaneously remember after the interaction with the ChatGPT, without any visual support or the possibility to check the information in the conversation with the tool.

Unlike the multiple-choice format used in the quantitative analysis, these open responses reduced the possibility of guessing or selecting a correct answer by chance. Even if an option such as "I don't remember" would have been provided, some participants might still have tried to guess the right answer. This qualitative insight thus serves as a simple and limited complement to the quantitative data, offering a more nuanced view of how confident participants were concerning what they think they remembered after their search.

- **First search : Shure and Audio-Technica Headphones**

Among the 102 responses received, the majority were vague or incorrect elements and only a few participants gave a correct and justified answer. The word "think" (or its French equivalent) appeared several times in responses, reflecting low confidence or a blurred memory. A number of participants simply mentioned "headphone 2" or "the second one" without explicitly naming the brand name, which could suggest partial memorization, the participants being focused more on the order of presentation or format of the information rather than its content or that some participants simply wanted to complete the questionnaire quickly. Three participants gave no response and a minority explicitly stated they did not remember the information. Participants seemed to be more likely to attempt an answer than to clearly state that they did not remember or they may have believed they had retained the correct information even though that was not necessarily the case.

- **Second search : Kindle E-readers**

Unlike the first exercise on headphones, a significantly larger proportion of participants provided correct answers. In most cases, these were justified with relevant details. Most participants also took the time to explicitly name the models ("Signature Edition," "Paperwhite 2023"), rather than referring to a "first" or "second" model, as was frequently observed in the previous study.

However, a slightly higher number of responses clearly expressed forgetting or an inability to recall the differences, with explicit phrasing such as "I don't remember". Regardless of this, the correct responses for this case were more justified and more often correct compared to the previous exercise.

Among the participants who indicated that they already knew the answer to the question before conducting the search, several clearly stated that they did not remember it and in the case of the headphone task, some did not provide the correct answer.

V. Discussion

As a reminder, the main objective of this research is to explore the cognitive implications of using conversational artificial intelligence, particularly ChatGPT, in the context of product-related information search. While existing literature has extensively studied user satisfaction, adoption, and trust regarding AI-powered tools for instance, little attention has been given to their potential impact on memory retention. Another strand of research has examined the cognitive consequences of digital tools, particularly through concepts like the Google effect, transactive memory and cognitive offloading. Although these cognitive mechanisms were originally studied in relation to internet search, they are now starting to gain renewed attention due to the rise of AI in general. Through a quantitative design involving a short experimental task, this study tested five hypotheses, in order to explore whether reliance on tools, such as AI-powered chatbots, can affect consumers' memory in the context of product information. It investigates this relationship not only directly, but also through the mediating role of trust and the moderating influence of perceived information complexity, age, and education level.

Impact of the reliance on conversational AI on the non-assisted memory (H1)

The first hypothesis (H1) suggested that greater reliance on conversational AI, measured by the frequency of use and perceived convenience, would result in a decrease in unassisted memory of brand-related information. This hypothesis was based on an abundant literature regarding cognitive offloading (CDE) and digital amnesia, which shows that individuals tend to externalize memory tasks to digital tools when they are accessible, easy to use and perceived as reliable (Sparrow et al., 2011; Risko & Gilbert, 2016; Grinschgl et al., 2021).

However, the statistical analysis did not confirm this assumption. The Chi-square test did not reveal any significant relationship between the level of ChatGPT dependency and participants' ability to remember product information without help. In other words, respondents who were highly dependent on the tool were not significantly more likely to forget the brand name than those who were less so.

Several elements help to contextualize this result. The survey found that 94.1% of participants showed some form of dependence on ChatGPT, whether due to its ease of use, perceived convenience or regular use. This overwhelming predominance of dependency within the sample may have reduced the variance of the independent variable, making it difficult to statistically detect its influence on memory. In practical terms, the absence of a distinct group of low-dependency participants may have masked any potential relationship.

In addition, only 26.5% of participants were able to correctly recall the brand during the final memory task, while 70.6% thought they had retained the information. This gap between perceived and actual memory echoes the work of Fisher et al. (2019), which showed that individuals often tend to overestimate their knowledge after an online search. Similarly, Ward (2013) highlighted that access to information through familiar digital interfaces can generate an illusion of knowledge, where people believe they “know” simply because the tool has been used, not because the content has actually been integrated.

The lack of a significant relationship between dependency and memory may seem contradictory to the theories of cognitive offloading and the Google effect (Sparrow et al., 2011; Risko & Gilbert, 2016), which predict that increased externalization weakens amnesic encoding. One possible explanation is that the task used in this study (storing information produced after a brief interaction) may not have induced sufficient cognitive load to trigger a detectable discharge effect. As Dunn & Risko (2016) point out, cognitive discharge occurs when individuals feel that the mental cost of memorization exceeds that of delegation. While participants considered the product information to be unimportant, they may not have felt the need to consciously externalize it, thus making the measurement of dependency less predictive in this context.

Moreover, some research suggests that confidence in the reliability of the digital tool is essential for the cognitive discharge effect to manifest itself (Schooler & Storm, 2021). While the majority of participants perceived ChatGPT as a reliable tool, this does not necessarily mean that they relied on it for memorization tasks, especially if they did not consider the information important enough to remember. This nuance could partly explain the observed lag between a high use of the tool and the absence of a marked effect on memory. In addition, participants had not been explicitly instructed to store product information and were not given a goal for storing it. Therefore, the task may lack motivational relevance, reducing the likelihood of deep cognitive engagement. In the absence of a clear retention objective, individuals may not have actively encoded content, even though they had been using ChatGPT extensively. This situation is similar to incident learning, where the absence of deliberate intention to memorize often leads to lower retention.

From a practical point of view, this analysis has some limitations. First, the sample lacked diversity in terms of AI dependency, with the majority of participants already being frequent or committed ChatGPT users. This homogeneity resulted in an imbalance that limited the efficacy of the Chi-square test. Second, the dependency score combined several dimensions (such as frequency of use and perceived convenience), which may have masked more subtle behavioural differences. Third, given that the majority of participants were heavily dependent on ChatGPT, it was difficult to compare different user profiles. Finally, the memorization task may not have been difficult enough or engaging enough to fully activate memory, especially in an unsupervised online context.

Trust as a mediator H2

Hypothesis 2 proposed that confidence in conversational AI and the information it provides would mediate the relationship between AI dependence and unassisted memory, so that a higher level of confidence would reinforce the negative effect of dependence on memory performance. However, this assumption was not confirmed by the analyses. The JASP mediation test did not reveal any significant indirect effect of the confidence variable, indicating that in this sample, Trust did not significantly influence the relationship between ChatGPT dependency and unassisted recall.

This result may seem counterintuitive given the strong theoretical underpinnings of this hypothesis. Previous research has consistently identified trust as an essential driver of user behaviour and cognitive processing in human-AI interactions (Van Pinxteren et al., 2019; Siau & Wang, 2018; Shahzad et al., 2024). Specifically, it has been suggested that users who trust a chatbot or the information it provides are more likely to delegate certain cognitive tasks such as remembering or checking content, which reduces internal amnesic effort (Afroogh et al., 2024; Zhai, 2024). Consistent with this, the survey found that 81.4% of respondents considered ChatGPT a reliable tool. Yet, despite this high level of confidence, no significant mediating effect on memory performance was observed.

A possible explanation lies in the very characteristics of the memory task. Similar to the interpretation for H1, it is possible that the task was not perceived as a cognitively demanding or sufficiently motivating situation to encourage participants to actively encode information. As Risko and Gilbert (2016) point out, cognitive offloading is based on an individual cost-benefit assessment: people are more likely to delegate when they feel that the effort required to remember is greater than the convenience of delegation. In this study, participants did not have an explicit memory objective, which likely led to superficial treatment regardless of their confidence level. In this case, trust alone may not be sufficient to trigger active or passive cognitive delegation.

Another factor that may have limited the detection of a mediator effect is the lack of variance in participants' responses to the confidence scale. The majority of them gave a high score to the reliability of ChatGPT, which may have led to a ceiling effect, thus reducing the sensitivity of the analysis. Furthermore, the measure of confidence used in this study combined both confidence in the tool and confidence in the information it provides, while the literature points out that these dimensions can work differently (Baek & Kim, 2023; Shahzad et al., 2024). A finer distinction between these two aspects could perhaps have led to the identification of more specific channels of mediation.

From a theoretical point of view, these results invite us to reconsider the hypothesis of a linear relationship between trust and memory. While Zhai (2024) suggests that strong trust can encourage passive delegation and superficial treatment of information, the present results do not clearly confirm such a compromise. Trust alone may not be a sufficient condition for cognitive offloading to occur, especially in contexts where content appears trivial or the task is not personally relevant. This interpretation supports the argument of Menon and Shilpa (2023) that trust in AI is contextual, influenced by the complexity of the task and its perceived significance.

Although trust was a binary variable, it was treated as continuous for the purposes of the exploratory mediation analysis. This methodological choice provides only an approximate estimation of the indirect effect and may not capture the true nature of the mediator. Moreover, the relatively small and homogenous sample used in this study further constrains the robustness and generalizability of the results, calling for cautious interpretation.

Complexity of the information as a moderator H3

Hypothesis 3 proposed that the perceived complexity of information would moderate the relationship between conversational AI dependence and unassisted memory. Specifically, it was expected that when users perceive information as more complex, they would be more likely to rely on ChatGPT, resulting in greater cognitive discharge and, therefore, a lower autonomic memory retention. However, this hypothesis could not be rigorously tested due to statistical limitations in the dataset.

Specifically, the contingency tables used to examine the interaction between complexity, dependency and memory included several categories with extremely low numbers, which violated the conditions necessary to perform valid Chi-square tests. This has made it impossible to conduct a reliable moderation analysis within the current methodological framework. The lack of sufficient variability and distribution between different levels of perceived complexity limited the ability to detect an interactive effect, even if it existed. The sample size, although adequate for some analyses, was insufficient when distributed among the many categorical combinations required for a moderation analysis.

Descriptive data further highlights this limitation: only 2% of participants perceived ChatGPT's product information as complex. This figure reflects a lack of variability in perceived complexity, which has prevented any potential moderating effect from being observed. For future research, it would be relevant to voluntarily introduce greater variation in task complexity, ensuring that at least one condition involves more cognitively demanding content. However, such an approach would be more suitable for an experimental setting, where the level of difficulty can be controlled and introduced gradually without discouraging participation, as opposed to a general survey context.

From a theoretical standpoint, this is unfortunate, as some prior literature supports the idea that task complexity may influence cognitive offloading. Risko and Gilbert (2016) argue that individuals are more inclined to offload when the cognitive load of a task exceeds their working memory capacity. Similarly, Cheng et al. (2022) note that users tend to expect more assistance from conversational agents when information is complex or technical, which could reinforce reliance and potentially reduce memory engagement.

Age as a moderator (H4)

Hypothesis 4 proposed that age would moderate the relationship between conversational AI addiction and unassisted memory, assuming that this effect would be more pronounced in younger users, accustomed to delegating cognitive tasks to tools like ChatGPT. However, the analysis did not confirm this assumption. No significant difference was observed between younger and older participants regarding the effect of ChatGPT dependence on their ability to remember product information without assistance. In other words, age does not appear to significantly influence the relationship between addiction and memory performance.

This result may seem counter-intuitive to the generational trends highlighted in previous studies. Young adults are known to use ChatGPT more frequently, with global usage data indicating that individuals aged 18-34 represent over 60% of users (Statista, 2025; Semrush, 2025). The survey found that a majority of participants were young adults, but this predominance did not translate into a more pronounced cognitive delegation effect for older users.

One possible explanation for this is the composition of the sample. Older adults were under-represented, constituting only a small proportion of participants. This imbalance has probably limited the ability to observe a true generational contrast. In addition, even within the youngest group, the level of dependence was already very high, thus reducing variability and making it more difficult to detect a moderating effect. The homogeneity of the sample in terms of dependency could therefore mask any potential influence of age. Moreover, the study did not take into account very young users under 18 years of age, a population highly exposed to digital environments and likely to present distinct cognitive delegation patterns.

The absence of moderation by age also opens a broader reflection on cognitive strategies. While younger users are often assumed to rely more heavily on digital tools, they may also be better at integrating these tools into their information management practices without necessarily impairing memory. Conversely, older individuals may rely more on personal judgment and established cognitive routines, showing more resistance to digital delegation (Menon & Shilpa, 2023). However, in this study, older profiles were unfortunately too underrepresented to draw any reliable conclusion or confirm whether such a pattern could significantly influence the relationship between reliance and memory.

Education level as a moderator (H5)

Hypothesis 5 proposed that the level of education would moderate the relationship between conversational AI dependency and unassisted memory, assuming that individuals with a higher level of education would be less negatively affected by this dependence in terms of memory performance. However, this assumption was not confirmed by the results. Exploratory moderation analysis, based on Chi-square tests performed separately for two education level groups, did not reveal any significant relationship between AI dependence and unassisted memory, Whether in the lower education group or in the higher education group. These results indicate that, in this sample, the level of education did not significantly alter the impact of AI dependence on memory.

This result may seem counter-intuitive in the light of existing theoretical and empirical knowledge. Several studies highlight the role of the educational pathway in the development of advanced cognitive skills, particularly in critical thinking, reflection and metacognition (Walter, 2024). These skills are supposed to promote a more strategic use of AI tools, with a better ability to judge when it is relevant to rely on the tool or to call upon one's own cognitive resources. It therefore seemed plausible that a high level of education would act as a protective factor against the deleterious effects of memory dependence.

However, recent literature offers a more nuanced reading. While education provides the tools necessary for a critical assessment of digital technologies, it does not guarantee that they will always be used in a thoughtful or distanced manner. Salim Jr et al. (2023) show, for example, that even highly skilled professionals can develop some form of functional dependency on AI systems, especially when they routinely use them in low-demanding settings. Bai et al. (2023) go in the same direction, pointing out that immediate access to AI-generated responses can short-circuit analysis or reasoning processes, including in individuals with a strong academic background. In this light, education alone may not be sufficient to prevent the excessive use of AI if the context or motivation does not support active information processing.

Several factors may explain the lack of a moderating effect in this study. First, it is possible that the nature of the task, centred on recalling product-related information, did not require a sufficient level of cognitive engagement for the level of education to play a differentiating role. As with the previous assumptions, the task may not have been perceived as sufficiently demanding or personally relevant, which would have led to superficial treatment in all groups. Second, despite the distinction between levels of education, the sample was relatively homogeneous in terms of numerical familiarity, with both groups reporting frequent use of ChatGPT. This homogeneity may have mitigated potential intergroup differences in cognitive strategies.

From a theoretical point of view, these results suggest that education should not be seen as a fixed moderator of behaviour but rather as a variable among others, such as motivation, the context, complexity of the task or digital literacy, which shape interactions with AI. The absence of a significant moderating effect suggests that education alone is not sufficient to determine how AI addiction affects memory, especially in everyday or non-engaging contexts, where the user can put efficiency before thought.

Finally, it is worth pointing out the methodological limitations of this study. The education categories used were broad and may have masked more subtle differences between subgroups. In addition, the total sample size, although adequate for some analyses, may have lacked statistical power to detect a moderating effect. Future research could benefit from a more nuanced segmentation of education levels and the use of more cognitively demanding tasks, in order to better understand the interaction between the educational path and AI reliance behaviours.

Interaction between age and education level (H5bis)

Hypothesis 5b suggested that, although a high level of education may reduce the negative effects of conversational AI reliance, this moderating effect could be reduced in young adults still undergoing academic formation. However, this hypothesis could not be tested in the present study. It would have required an analysis of the interaction between two moderating variables, age and level of education, which was not feasible given the limited sample size. Performing subgroup analyses under these conditions would have compromised statistical power, and separate tests for age and level of education showed no significant moderating effect. Since the Chi-square test does not allow to model complex moderating effects, this hypothesis was treated in an exploratory way.

However, this reflection is consistent with recent studies that suggest that young users, including those in higher education, are particularly prone to automated uses of AI (Salim Jr et al., 2023; Bai et al., 2023). With many still consolidating their cognitive strategies, they may lack critical hindsight to assess when and how to delegate information processing to digital agents. This trend is further reinforced by the increasing use of tools such as ChatGPT in academic settings, where they are increasingly integrated into daily study practices. As a result, even students with some academic experience can delegate mental effort to ChatGPT in a way that impairs active memorization.

This suggests a nuanced paradox: although education is supposed to equip individuals with the tools necessary for critical thinking, these tools could have limited impact on memory in young adults still in cognitive development, evolving in a culture marked by digital immediacy. Future research could explore whether this gap between educational potential and actual cognitive engagement tends to narrow over time, or if prolonged exposure to tools such as ChatGPT reinforces automated thinking patterns despite academic advancement.

In conclusion, none of the hypotheses tested in this exploratory study were confirmed, and two could not be adequately assessed due to statistical limitations. However, this absence of significant or conclusive results does not mean the topic should be dismissed. On the contrary, it highlights the inherent complexity of measuring cognitive effects related to AI use, as well as the need for more robust methodological approaches.

The small sample size, combined with a lack of diversity, particularly in terms of age and education, likely limited the ability to detect meaningful relationships or moderation effects. Future research, based on larger and more heterogeneous samples and using methods better suited to analyzing interaction effects and mediation mechanisms, will be necessary to fully understand how reliance on conversational AI influences memory processes in everyday digital contexts.

VI. Conclusion

6.1. Short Summary

In the digital era, people are living in an environment saturated with information and technology, where artificial intelligence tools are becoming increasingly important in everyday life. ChatGPT, in particular, is seeing massive adoption in a variety of areas, facilitating access to information, decision support and automation of exchanges. This transformation of practices nevertheless raises new questions about the cognitive effects of these technologies, particularly on how individuals mentally store, process or delegate information.

This thesis explores the cognitive implications of using conversational artificial intelligence, in particular ChatGPT, to search for product information. Based on the literature on digital amnesia and cognitive externalization, the study aims to analyse whether reliance on these tools affects consumers' unassisted memory. A model incorporating five hypotheses was tested from a questionnaire including a brief experimental task, mobilizing variables such as confidence in the tool, perceived complexity of information, age and level of education.

The results did not confirm any of the hypotheses tested, although some trends were observed. No significant relationship was established between ChatGPT reliance and unassisted memory performance, nor between this relationship and the mediation or moderation variables studied. These results may be explained by a lack of diversity within the sample, an unengaging memorization task, and a lack of explicit motivation to retain information.

However, the study highlights the difficulty of measuring the cognitive effects of AI and calls for future research with larger samples and more controlled experimental devices. It is thus positioned as a first exploratory step aimed at better understanding the effects of conversational AI on memory processes in digital environments.

6.2. Managerial implications of your study

The results of this study, although no hypothesis has been confirmed statistically, highlight several trends that could be of concern. While a majority of participants report that they trust AI and use it frequently, particularly to search for product information, this is already evidence of a change in access to information behaviours. Without being able to confirm, it is possible that tools such as conversational agents could be used as more advanced search engines, such as for searching product information, but can also compare them, provide advice based on, for example, end-use, more personalized responses. This development could therefore suggest a gradual loss of control and visibility for brands. Indeed, if some consumers are starting to favour the use of conversational agents like ChatGPT at the expense of more traditional sources such as Google, for which companies usually invest in SEO or paid strategies (SEO/SEA) to highlight their official website. In the long run, this could mean that these platforms once central to brands' digital strategy would become secondary, at least in certain phases of the customer journey.

This phenomenon is all the more important to take into account from a managerial point of view because if artificial intelligence seeks its information on the Internet, brands do not necessarily have direct control over the data relayed by these tools. Thus, brands could see their speech distorted, summarized or filtered without having the possibility to fully control it. This raises the need for companies to think about strategies to better feed the databases or sources that these IAs use. Although it is not yet possible to say with certainty that this scenario will be imposed or on what scale, it is a relevant line of thought to consider, in an perspective of strategic anticipation.

Thus, the design and use of chatbots could also be revised to reduce, at least in part, these potential cognitive effects. The objective should not only be to facilitate access to information, but also to encourage active encoding of information. This could involve interactions that actively solicit the user's memory, such as reformulations, interactive summaries or the use of storytelling. The introduction of so-called «cognitive nudge» mechanisms would make it possible to combat the systematic externalisation of memory induced by AI.

6.3. Theoretical implications of your study

The fact that the hypotheses tested in this study were not confirmed should not questions the relevance of this topic. On the contrary, it highlights the importance of reexamining existing conceptual model and adapting methodologies to better understand the complexity of cognitive effects associated with the use of conversational artificial intelligences. These points will be developed in the next section, which is devoted to the limits of the study and the possible avenues for future research. Furthermore, the purpose of this research was not to prove a causal link but rather to explore their possibility.

From a theoretical point of view, the results obtained can reinforce the idea that the link between artificial intelligence and memory deserves more attention. The literature review has highlighted key concepts, suggesting a growing interest in this filed of study.

Then, the fact that many participants showed signs of a strong reliance on ChatGPT, based on the perceived convenience the perceived ease of use and their frequency of usage, indicates that this type of tool could be perceived, implicitly, as an extension of their own memory. Although the present study did not demonstrate a direct link between this dependence and a measurable impairment of unassisted memory, this does not exclude the existence of a real phenomenon. It is possible that different methodologies or more engaging contexts of use reveal effects that were not yet detected.

This research helps to open up a field of thinking that is still emerging, namely the interactions between memory, humans and artificial intelligence. It invites us to consider that the relationship to information is changing profoundly, not only in the way it is consulted but also in the way it is stored or delegated.

6.4. Limitations and suggestions for future research

This exploratory study has several methodological and empirical limitations that must be taken into account, while opening up interesting perspectives for future research.

First, the relatively small size of the sample limited the statistical power of some analyses, especially to test moderation effects involving cross-variables (e.g. H3 and H5b). Thus, some assumptions could not be properly evaluated. Future studies would benefit from a larger and more heterogeneous sample to allow robust analysis of complex interactions between variables.

In addition, the sample was poorly diversified in terms of age and level of education, with the majority of participants being young adults undergoing training. This homogeneity limits the generalization of results to other population profiles. It would be relevant in future research to integrate more diverse age groups and contrasting levels of education to examine whether the observed effects vary by generation or cognitive capital.

In order to ensure a more balanced diversification of certain socio-demographic variables, such as age, it would have been appropriate to consider a quota sampling method. For example, based on Statista data on the distribution of ChatGPT users by age group, it would have been possible to define proportional quotas for each group. This approach would have ensured a minimum number of participants in each age group, allowing for a more robust comparison of effects across generations. Such a strategy would have strengthened the representativeness of the sample in relation to the target population of conversational AI users and would have allowed for a more detailed exploration of possible age-related moderating effects.

Another barrier to the detection of significant effects is the low variance observed in ChatGPT confidence responses. The majority of participants expressed a high level of confidence, which may have led to a cap effect and reduced sensitivity of the mediation tests. Furthermore, the measure used did not sufficiently distinguish between confidence in the tool and confidence in the information provided, whereas the literature suggests that these dimensions may act differently. It would therefore be useful, in the future, to separate these components in the operationalization of the "confidence" variable.

Moreover, the very nature of the amnestic task proposed in the survey may have limited participants' cognitive engagement. The absence of an explicit purpose for storage may have encouraged superficial processing of information, regardless of the level of trust or reliance. Future research could propose more engaging or contextualized tasks, for example by integrating decision or purchase objectives, in order to better capture the effects on memory.

From a methodological point of view, some variables were treated as approximations. The confidence variable, although originally binary, was used as a continuous variable in the mediation analysis, which may have skewed the interpretation of indirect effects. Particular attention should be paid to the rigour of the measures used and their adequacy with the statistical tests envisaged.

It would also have been relevant to rely on a scale recently developed by Tao, Zhang and Liu (2024), which although oriented towards creative processes, deals in depth with the phenomenon of cognitive externalization vis-à-vis artificial intelligence. This 30-item scale explores five complementary dimensions of cognitive AI use: credulity, dependency, irrationality, perceived reliability, and cognitive autonomy. Even if it was designed for the field of creativity, its conceptual framework is very close to the problem discussed here and could, with some adjustments, have been adapted to the context of storing product-related information. The integration of such a tool would potentially have made it possible to measure cognitive delegation more precisely, while strengthening the methodological quality of the analyses carried out.

Moreover, the selection of a collection method based on an online self-administered questionnaire has its own limitations: low control over the context of the survey, risks of distraction or multitasking, and potential for self-reporting bias. The inclusion of a minimal experimental component has partially overcome this limitation, but future research could use more structured experimental arrangements to reinforce internal validity. This type of controlled protocol is also widely preferred in studies on memory within the existing literature, because it allows to better frame the course of tasks and limit contextual bias. In a laboratory or in a supervised digital environment, it is indeed possible to control critical variables such as distractions, multitasking or cheating behaviours (such as checking again or verifying the information via AI). In this study, the lack of control inherent to online procurement may have hampered the fine interpretation of results, particularly with regard to the actual measurement of unassisted memory.

The measurement of unassisted memory, finally, was based on a spot evaluation carried out in hot mode, without taking into account the delayed recall. It would be appropriate to introduce longitudinal measurements or deferred assessments to examine the effect of reliance on AI on longer-term memory.

Finally, other explanatory variables have not been integrated into the model, such as confidence in one's own judgment, cognitive style, numerical self-efficacy or AI consultation habits. These dimensions could enrich the understanding of cognitive delegation mechanisms and their effects on memory. For example, it would be particularly interesting to examine the role of self-confidence in memorization. Although the results of this study did not demonstrate a direct effect on retention, it is notable that many participants reported feeling as if they remembered the information when their answers were incorrect. This suggests a form of mnesic illusion: some actually no longer remembered the content despite an impression of mastery, while others thought they had memorized the correct answer when it was an error. This dissociation between subjective perception and objective performance could reflect a significant metacognitive bias, which would be useful to deepen in future research.

It would have also been possible to broaden the scope of research by focusing more specifically on using ChatGPT or other conversational agents to search for information about particular brands. This would have made it possible to examine not only the effects on memory, but also on the perception of the brand and its image. An interesting track would also have been to integrate a brand chatbot, based on artificial intelligence, in an experimental protocol to directly assess the impact of interaction with this tool on the memory of transmitted information and on consumers' attitudes towards the brand concerned.

In conclusion, this study highlights the methodological challenges related to the analysis of cognitive effects of AI in an applied framework. It paves the way for more in-depth research, combining more diverse samples, rigorous experimental protocols, and more comprehensive theoretical models to better understand the impact of conversational artificial intelligence on human memory.

VII. Appendices

1) Appendix 1: the survey

- **Page 1 :**

As part of my Master's thesis in International Strategic Marketing at HEC Liège, I am conducting a study on the use of AI-based conversational agents.
Thank you in advance for your participation.
Please note that the time required to complete the research and answer the questions may take up to 15 minutes.

Before answering the questionnaire, you will need to perform several searches on ChatGPT. Please read the instructions thoroughly first before starting the searches.

Instructions:
1. Open a new conversation with ChatGPT.
2. In this conversation, as a consumer, you should search for the following information:

- ***You are hesitating whether to buy an Audio-Technica headset or a Shure headset, but you don't know which one is more suitable for prolonged use.***
- ***You are hesitating whether to buy the Kindle Paperwhite 2023 or the Paperwhite Signature Edition, but you don't*** **know the difference between the two.**

3. Read the responses provided by ChatGPT.

4. Clear the conversation from your history or close the page and do not return to it while answering the questionnaire.

The goal is to assess how you interact with ChatGPT and how you perceive the quality of the answers provided.
Once the search is completed, please answer the following questions.

- **Page 2:**

*Did you make sure to close the page or tab containing ChatGPT or clear the conversation after your research?**

- *Yes*
- *No*

- **Page 3 :**

Please indicate to what extend you agree with the following statements regarding the responses provided by ChatGPT during your search : (1 = Strongly disagree ; 5 = Strongly agree)

1. *The answers provided by ChatGPT were very easy to understand.*
2. *The information given by ChatGPT did not require much effort to be understood.*
3. *The wording of the answers was simple.*
4. *Getting a response from ChatGPT did not require advanced knowledge.*

- **Page 4 :**

Please indicate to what extend you agree with the following statements regarding the responses provided answers provided by Artificial Intelligences in general: (1 = Strongly disagree ; 5 = Strongly agree)

1. *I generally trust the answers provided by artificial intelligences.*
2. *I find that the information given by artificial intelligences is generally credible.*
3. *I trust the recommendations made by artificial intelligences.*

Please indicate to what extend you agree with the following statements regarding the responses provided by ChatGPT in particular,: (1 = Strongly disagree ; 5 = Strongly agree)

1. *I generally trust the answers provided by ChatGPT.*

2. *I find that the information given by ChatGPT is generally credible.*
3. *I trust the recommendations made by ChatGPT.*

- **Page 5 :**

How often do you use ChatGPT to search for information about a product? (For example: reading reviews, comparing products, finding the best product on the market, solving a product-related problem, etc.)

- Never
- Rarely (1–2 times a month)
- Sometimes (once a week)
- Often (several times a week)
- Very often (almost every day)

Please indicate to what extend you agree with the following statements regarding the responses the reasons why you use ChatGPT: (1 = Strongly disagree ; 5 = Strongly agree)

1. *I use ChatGPT because it is convenient.*
2. *I use ChatGPT because I can get the information I need with less effort.*
3. *I use ChatGPT because I can use it anytime, anywhere.*

Please indicate to what extend you agree with the following statements regarding the information search you just performed on ChatGPT: (1 = Strongly disagree ; 5 = Strongly agree)

1. *The information search was very easy to perform.*
2. *It required little effort.*
3. *It was a simple task.*

Please indicate to what extend you agree with the following statements about your preference for using ChatGPT compared to other sources (official websites, online reviews, shopping channels, customer service, etc.): (1 = Strongly disagree ; 5 = Strongly agree)

1. *I will always prefer using ChatGPT to search for information about a brand or product over other sources (official website, online reviews, customer service...).*
2. *I will continue to prefer ChatGPT because of its features (such as ease of use, speed, availability, etc.) compared to other sources.*
3. *I will always favour ChatGPT for getting information about a brand or product because of the quality of its answers.*
4. *I will always choose to use ChatGPT rather than other sources when searching for information about a brand or product.*

- **Page 6 :**

Please indicate to what extend you agree with the following statements regarding the responses provided by ChatGPT : (1 = Strongly disagree ; 5 = Strongly agree)

1. *Are you certain that you remember the information correctly ?*
2. *Are you sure that you can recall this information from memory?*
3. *Are you confident in your ability to remember this information ?*

- **Page 7 :**

Note : If you don't remember, just say ''I don't remember''

1. *Based on what you found, which headset would you recommend to someone planning to wear it for a long time, and why?*
   (Open-ended question)
2. *Before conducting this search on ChatGPT, did you already know the answer to this question?*

- *Yes*
- *No*

- **Page 8 :**

1. *What is/are the difference(s) you remember between the two Kindle models ?*
2. *Before conducting this search on ChatGPT, did you already know the answer to this question?*

- *Yes*
- *No*

- **Page 9 :**

1. *Based on what you read in ChatGPT, which of the two headsets is recommended for prolonged use and why?*

- *The Audio-Technica headset is preferred for its better sound isolation, which reduces auditory fatigue.*
- *The Shure headset is recommended because it has a longer Bluetooth battery life.*
- *The Audio-Technica headset is often recommended for long sessions due to its comfort and lighter weight.*
- *The Shure headset is recommended for long listening sessions because of its neutral frequency response, which reduces auditory fatigue.*

2. *What is one of the major differences between the classic 2023 Paperwhite and the Signature Edition?*

- *The Signature Edition is waterproof, while the classic version is not.*
- *The Signature Edition has wireless charging and an adaptive brightness sensor.*
- *The classic Paperwhite has a larger memory than the Signature Edition.*
- *Both models are identical, with only the color changing.*

- **Page 10:**

1. How old are you?

- Under 18 years old
- Between 18 and 24 years old
- Between 25 and 34 years old
- Between 35 and 44 years old
- Between 45 and 54 years old
- 55 years old and over

2. What is the highest level of education you have completed?

- No diploma
- High School (CESS, Bac...)
- Bachelor's degree
- Master's degree
- Other, please specifiy

2) Appendix 2 : the reliability scales

- Convenience

Unidimensional Reliability

Frequentist Scale Reliability Statistics

			95% CI	
Coefficient	Estimate	Std. Error	Lower	Upper
Coefficient α	0.724	0.067	0.592	0.856

Frequentist Individual Item Reliability Statistics

	Coefficient α (if item dropped)		
Item	Estimate	Lower 95% CI	Upper 95% CI
CONV_1	0.643	0.381	0.904
CONV_2	0.594	0.422	0.767
CONV_3	0.676	0.452	0.900

- Easiness

Unidimensional Reliability

Frequentist Scale Reliability Statistics

			95% CI	
Coefficient	Estimate	Std. Error	Lower	Upper
Coefficient α	0.924	0.044	0.839	1.009

Frequentist Individual Item Reliability Statistics

	Coefficient α (if item dropped)		
Item	Estimate	Lower 95% CI	Upper 95% CI
EASE_1	0.884	0.824	0.943
EASE_2	0.873	0.659	1.086
EASE_3	0.912	0.744	1.080

- Loyalty

Unidimensional Reliability

Frequentist Scale Reliability Statistics

Coefficient	Estimate	Std. Error	95% CI Lower	95% CI Upper
Coefficient α	0.899	0.018	0.863	0.934

Frequentist Individual Item Reliability Statistics

	Coefficient α (if item dropped)		
Item	Estimate	Lower 95% CI	Upper 95% CI
LTY_1	0.865	0.818	0.911
LTY_2	0.922	0.886	0.959
LTY_3	0.841	0.785	0.898
LTY_4	0.847	0.791	0.902

- Trust in AI

Unidimensional Reliability

Frequentist Scale Reliability Statistics

Coefficient	Estimate	Std. Error	95% CI Lower	95% CI Upper
Coefficient α	0.800	0.045	0.711	0.889

Frequentist Individual Item Reliability Statistics

	Coefficient α (if item dropped)		
Item	Estimate	Lower 95% CI	Upper 95% CI
TAI_1	0.670	0.508	0.831
TAI_2	0.753	0.613	0.894
TAI_3	0.753	0.614	0.892

- Trust in ChatGPT

Unidimensional Reliability

Frequentist Scale Reliability Statistics

Coefficient	Estimate	Std. Error	95% CI Lower	95% CI Upper
Coefficient α	0.811	0.064	0.686	0.936

Frequentist Individual Item Reliability Statistics

Item	Coefficient α (if item dropped) Estimate	Lower 95% CI	Upper 95% CI
TGPT_1	0.737	0.483	0.992
TGPT_2	0.758	0.522	0.994
TGPT_3	0.728	0.579	0.877

- Complexity of the information

Unidimensional Reliability

Frequentist Scale Reliability Statistics

Coefficient	Estimate	Std. Error	95% CI Lower	95% CI Upper
Coefficient α	0.716	0.056	0.605	0.826

Frequentist Individual Item Reliability Statistics

Item	Coefficient α (if item dropped) Estimate	Lower 95% CI	Upper 95% CI
CPLX_1	0.711	0.598	0.824
CPLX_2	0.623	0.449	0.796
CPLX_3	0.585	0.439	0.731
CPLX_4	0.697	0.545	0.850

3) Appendix 3 : validity of the scales

4) Appendix 4 : descriptive statistics

Binomial Test ▼

Variable	Level	Counts	Total	Proportion	p
MEM_DV	0	75	102	0.735	< .001
	1	27	102	0.265	< .001
RLC_IV	0	6	102	0.059	< .001
	1	96	102	0.941	< .001
TRST_MED	0	12	102	0.118	< .001
	1	90	102	0.882	< .001
CPLX	0	100	102	0.980	< .001
	1	2	102	0.020	< .001
Age	1	1	102	0.010	< .001
	2	57	102	0.559	0.276
	3	26	102	0.255	< .001
	4	4	102	0.039	< .001
	5	6	102	0.059	< .001
	6	8	102	0.078	< .001
Edu	3	45	102	0.441	0.276
	4	39	102	0.382	0.022
	5	18	102	0.176	< .001
EASE	0	3	102	0.029	< .001
	1	99	102	0.971	< .001
LTY	0	61	102	0.598	0.059
	1	41	102	0.402	0.059
SCF	0	30	102	0.294	< .001
	1	72	102	0.706	< .001
FREQ_Raw	1	30	102	0.294	< .001
	2	32	102	0.314	< .001
	3	13	102	0.127	< .001
	4	13	102	0.127	< .001
	5	14	102	0.137	< .001
CONV	0	5	102	0.049	< .001
	1	97	102	0.951	< .001
TAI	0	19	102	0.186	< .001
	1	83	102	0.814	< .001
TGPT	0	13	102	0.127	< .001
	1	89	102	0.873	< .001
CLSD_1	0	71	102	0.696	< .001
	1	31	102	0.304	< .001
CLSD_2	0	28	102	0.275	< .001
	1	74	102	0.725	< .001

Note. Proportions tested against value: 0.5.

5) Appendix 5 : statistical analysis

- H1

Contingency Tables

	MEM_DV		
RLC_IV	0	1	Total
0	5	1	6
1	70	26	96
Total	75	27	102

Note. Each cell displays the observed counts

Chi-Squared Tests

	Value	df	p
X^2	0.315	1	0.575
N	102		

- H2 : Mediation Analysis

Direct effects

							95% Confidence Interval	
			Estimate	Std. error	z-value	p	Lower	Upper
RLC_IV	→	MEM_DV	0.103	0.188	0.549	0.583	-0.265	0.472

Note. Estimator is ML.

Indirect effects

									95% Confidence Interval	
					Estimate	Std. error	z-value	p	Lower	Upper
RLC_IV	→	TRST_MED	→	MEM_DV	9.278×10^{-4}	0.031	0.029	0.976	-0.061	0.063

Note. Estimator is ML.

Total effects

			Estimate	Std. error	z-value	p	95% Confidence Interval Lower	Upper
RLC_IV	→	MEM_DV	0.104	0.185	0.562	0.574	-0.259	0.467

Note. Estimator is ML.

Path coefficients

			Estimate	Std. error	z-value	p	95% Confidence Interval Lower	Upper
TRST_MED	→	MEM_DV	0.004	0.137	0.029	0.976	-0.265	0.273
RLC_IV	→	MEM_DV	0.103	0.188	0.549	0.583	-0.265	0.472
RLC_IV	→	TRST_MED	0.229	0.134	1.714	0.086	-0.033	0.491

Note. Estimator is ML.

R-Squared

	R^2
MEM_DV	0.003
TRST_MED	0.028

- Moderator analysis : H3 (filter 1)

Contingency Tables

	RLC_IV		
MEM_DV	0	1	Total
0	5	69	74
1	1	25	26
Total	6	94	100

Note. Each cell displays the observed counts

Chi-Squared Tests

	Value	df	p
X^2	0.289	1	0.591
N	100		

- Moderator analysis : H4 (filter 1)

Contingency Tables

	RLC_IV		
MEM_DV	0	1	Total
0	3	57	60
1	1	23	24
Total	4	80	84

Note. Each cell displays the observed counts

Chi-Squared Tests

	Value	df	p
X^2	0.026	1	0.871
N	84		

- Moderator analysis : H4 (filter 2)

Contingency Tables

	RLC_IV		
MEM_DV	0	1	Total
0	2	13	15
1	0	3	3
Total	2	16	18

Note. Each cell displays the observed counts

Chi-Squared Tests

	Value	df	p
X^2	0.450	1	0.502
N	18		

- Moderator analysis : H5 (filter 1)

Contingency Tables

	RLC_IV		
MEM_DV	0	1	Total
0	2	31	33
1	0	12	12
Total	2	43	45

Contingency Tables

	RLC_IV		
MEM_DV	0	1	Total

Note. Each cell displays the observed counts

Chi-Squared Tests

	Value	df	p
X^2	0.761	1	0.383
N	45		

- Moderator analysis : H5 (filter 2)

Contingency Tables

	RLC_IV		
MEM_DV	0	1	Total
0	3	39	42
1	1	14	15
Total	4	53	57

Note. Each cell displays the observed counts

Chi-Squared Tests

	Value	df	p
X^2	0.004	1	0.951
N	57		

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EXECUTIVE SUMMARY

In today's digital era, individuals evolve in an environment saturated with information and technologies, where artificial intelligence tools are increasingly integrated into daily life. Among these, ChatGPT has seen rapid and widespread adoption across various domains, facilitating information access, decision-making support, and the automation of interactions. However, this transformation of usage patterns raises new questions regarding the cognitive implications of such technologies, particularly in terms of how individuals store, process, or delegate information.

This thesis investigates the cognitive effects of relying on conversational artificial intelligence, specifically ChatGPT, for searching product-related information. Grounded in the literature on digital amnesia and cognitive offloading, the study aims to determine whether dependence on these tools influences consumers' non-assisted memory. A conceptual model comprising five hypotheses was tested through a questionnaire including a brief experimental component. Variables such as trust in the tool, perceived complexity of the information, age, and educational level were examined.

The findings did not confirm any of the hypotheses tested, although certain tendencies were observed. No significant relationship was found between reliance on ChatGPT and non-assisted memory performance, nor with the mediating or moderating variables considered. These results may be partly attributed to a lack of sample diversity, the limited engagement of the memorization task, and the absence of explicit motivation to retain information.

Nonetheless, this study underscores the complexity of assessing the cognitive impacts of AI technologies and highlights the need for further research involving more diverse samples and controlled experimental settings. It thus constitutes a preliminary exploratory step toward a better understanding of how conversational AI may influence memory processes in digital contexts.

KEYWORDS: Artificial Intelligence, Conversational AI, ChatGPT, non-assisted memory, cognitive offloading, digital amnesia, exploratory quantitative study, memory retention

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