AI Literacy: A Prerequisite for Effective Use of Generative AI

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ABSTRACT

The widespread adoption of generative artificial intelligence (GenAI) tools such as ChatGPT is transforming professional and personal workflows. While these tools promise increased productivity and innovation, they also introduce risks related to job displacement, overreliance, and emotional discomfort. This thesis investigates a critical yet underexplored issue: the distinction between *use* and *correct use*. Specifically, it explores AI literacy by examining its constituent variables and analyzing how AI literacy relates to the correct use of generative AI tools. To investigate these dynamics, the central research question guiding this study is: *To what extent does AI literacy affect intentions of use and perceptions of* GenAI*?*

This thesis argues that technical skills alone are insufficient for meaningful engagement with GenAI. Instead, *effective use* depends on metacognition (awareness of one's cognitive processes) and anticipation (the ability to foresee limitations in model outputs). Emotional variables such as trust and xenophobia are examined as potential mediators of workplace acceptance and the perception that using AI "feels like cheating" is also briefly explored, as GenAI challenges traditional motivational theories.

A quasi-experimental design was employed. Participants completed self-report measures and a performance-based prompting task, using ChatGPT to plan a trip. Prompts were evaluated using a custom rubric grounded in theory and best practices from prompt engineering. Results revealed a misalignment between perceived and actual AI literacy: 25% of participants scored only 1 out of 10 on the prompt task, despite reporting high levels of AI literacy. Metacognition and anticipation were found to be naturally embedded within existing AI literacy constructs, contributing to its conceptual refinement. However, self-reported AI literacy did not significantly predict GenAI acceptance, and mediation analyses showed that trust and xenophobia did not significantly mediate this relationship. These findings highlight the need to refine how AI literacy is conceptualized and measured, and they caution against overreliance on self-reports in designing effective training programs and workplace policies.

KEYWORDS: AI literacy, prompt evaluation, metacognition, anticipation, generative AI, human-AI interaction, practical implementation of GenAI

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Introduction: Living With Generative AI

The integration of generative AI (GenAI) into (workplace) processes is fundamentally reshaping human - machine collaboration (Fatunmbi, 2023, p. 49). Tools like ChatGPT, Midjourney, and GitHub Copilot are now embedded in a range of workflows - and in doing so, they are changing how people perceive tasks, define their value, and motivate themselves (Cohran, 2025). GenAI is also redefining how humans *interact* with technology (Yi, 2021, p. 359). Fatunmbi (2023, pp. 51-57) describes this shift as an evolution in human-AI dynamics, moving beyond automating routine tasks and toward augmenting human intelligence. As such, AI enhances creative problem-solving and supports complex decision-making.

Before advancing further, it is essential to clarify what is meant by *artificial intelligence* (AI) and, more specifically, *generative AI* (GenAI), as this distinction underpins the entire thesis. Accordingly, this thesis adopts Koenig's (2024, p. 1333) definition of AI, as systems with rules for processing data from their environment to produce pre-specified, goal-directed outputs. Within this broad category, GenAI refers to a specific class of AI systems designed to create unique content (e.g. text, images, or code) based on patterns learned from large datasets (Aydin & Karaarslan, 2023). Aydin and Karaarslan (2023, p. 118) emphasize that the potential applications for GenAI are limitless. This thesis supports that view, while emphasizing that the true limit lies in an individual's prompting abilities, which are reflected in their level of AI literacy.

As these tools become more understood, advanced, and accessible, their use is spreading rapidly across industries. However, individual understanding and adoption of GenAI vary widely. Long and Magerko (2020, p. 2) argue that AI literacy - the successor to digital literacy - is a key determinant of how people use, evaluate, and trust such systems. This thesis builds on that premise and expands the definition of AI literacy to include metacognition, that is, awareness of one's thought processes and anticipatory competence as essential dimensions. Without such skills, users may misuse GenAI - even while falsely appearing AI literate - or reject AI systems altogether.

Shifting Human-Machine Dynamics

Two years ago, in 2023, the research of Eloundou, Manning, Mishkin, and Rock (2023, p. 1) estimated that 80% of the U.S. workforce *may* be impacted by GenAI, with approximately 19% of workers seeing over 50% of their tasks exposed - signalling a significant risk of job transformation, redundancy, or skill displacement. While this forecast painted a broad picture of a potentially dystopian future, it took less than a year for industry-specific projections to reflect similarly disruptive scenarios. In a 2024 report, *The Wall Street Journal* cites research from Forrester estimating that up to 32,000 advertising jobs in the U.S. - nearly 8% of the sector's workforce - could be eliminated by 2030 as GenAI automates core creative and strategic functions (Vranica, 2024). These projections are not hypothetical; they are grounded in historical adoption trends, current automation capabilities, and predictive modelling widely used in labour economics.

While these forecasts originate from the United States (U.S.), they are likely to mirror trends in other advanced economies, particularly in Western Europe, where industries and labour markets are increasingly interconnected. Given the global influence of U.S. tech firms and market benchmarks like the S&P 500, the implications of GenAI adoption are expected to be similarly disruptive across OECD countries. The fact that such aggressive figures have emerged within a year underscores the speed and scale at which GenAI is expected to reshape the modern workplace. As projections grow more threatening, they naturally spark widespread fear and anxiety among workers. Yet paradoxically, research and real-world practices suggest that a key determinant of GenAI 's utility is the level of confidence humans place in these systems (Eloundou et al., 2023, p. 22). This psychological contradiction - between trusting tools that simultaneously evokes uncertainty and an existential concern - highlights the need for intentional, emotionally sustainable integration strategies, including transparency, education, and the development of AI literacy.

Societal Relevance

Understanding how current and future employees perceive and engage with GenAI is essential for facilitating its meaningful integration into (workplace) processes. This is a central component of the thesis's societal relevance. GenAI challenges the long-standing assumption that "humans only communicate with humans" (Yi, 2021, p. 359). On one hand, it offers the potential to boost productivity, spark creativity, and reshape (the availability of) knowledge (Long & Magerko, 2020). On the other hand, it raises concerns around deepfakes, algorithmic bias, digital privacy, and security (Kong et al., 2021). Further, we know that segments of the population exhibit reluctance or scepticism toward GenAI due to deep-seated fears, misunderstandings, or lack of trust. Psychological phenomena such as xenophobia and the Uncanny Valley - in which human-like machines cause discomfort- pose significant challenges to public acceptance and can lead to rejection or avoidance (Wu, 2023).

While (generative) AI may feel new in public discourse, rule-based algorithmic systems have supported business operations for decades. What sets modern AI - particularly machine learning and generative models - apart is its ability to learn from data, adapt, and produce outputs beyond predefined instructions. This capacity, especially in GenAI, can give rise to the false impression that these systems are sentient. Their ability to generate human-like content has rapidly amplified both the possibilities and the anxieties surrounding automation. Now, the rise of agentic AI - systems capable of autonomous decision-making and goal pursuit - marks the next frontier. As agentic AI grows more powerful and GenAI more widespread, society cannot afford to meet them with fear, avoidance, or cognitive unpreparedness (Koenig, 2024, p. 1342). This urgency elevates AI literacy to a central pillar of both educational strategies and workplace development.

This study places particular emphasis on the digitally native Generation Z (Gen Z) demographic, who are entering the workforce with high expectations for digital tools and unique anxieties about automation. While this generation may appear naturally equipped to work with AI, in most cases they lack the structured training or reflective insight necessary for responsible, confident, and productive adoption.

Academic Relevance

This thesis contributes to academic literature by addressing multiple interdisciplinary calls for research into the psychological, educational, and societal dimensions of GenAI and its adoption. At its core, the study advances the conceptualization of AI literacy - not just as the ability to use and evaluate AI systems (Yi, 2021, p 359 -360), but as a multidimensional construct incorporating metacognitive awareness and anticipatory competence. In doing so, it directly addresses Fernandes and colleagues, (2024), call to explore the misalignment between users' performance with AI tools and their metacognitive insight.

Further, this research explores the psychological factors that shape user engagement with GenAI, including trust, fear, and algorithm aversion. Building on Dietvorst et al.'s (2015) work, it investigates whether rejection of algorithmic decision-making also applies to humanlike outputs generated by tools such as ChatGPT. It also expands on Wu's (2023) master's thesis on the "social uncanny valley", by exploring other kinds of AI generated outputs. Where Wu's (2023) research focused on art, this research focuses on text to further look into the phycological dynamics leading to avoidance or acceptance.

This thesis also responds to Hong's (2021) recommendation to investigate how humanlike versus mechanical performances by AI systems influence user trust, particularly when operational expectations are violated. By focusing on Gen Z, a group often assumed to be digitally fluent, the study contributes new empirical data on how user expectations interact with perceived AI competence.

In terms of application, the thesis aligns with Long and Magerko's (2020) call for learner-cantered and workplace-relevant AI education. It provides actionable insights for the development of training programs and proposes an outline for an AI Literacy Course (available in Appendix A) that enhance AI understanding, responsible use, and user confidence in professional contexts. These educational implications are especially important as this generation enters the workforce with high expectations for digital fluency but limited structured exposure to AI systems. Finally, the research contributes to Aydin and Karaarslan's (2023) broader agenda: to understand the ethical and societal implications of these technologies.

Research Question

To contribute to ongoing discussions around GenAI, outlined in the societal and academic relevance sections, this thesis extends the investigation on AI literacy, focusing on the components that constitute it in order to better understand its emergence. On a practical level, it examines the gap between perceived literacy and the demonstrated ability to use GenAI effectively. This thesis also explores factors such as trust**,** xenophobia toward AI**,** and the perception that using GenAI "feels like cheating", thus also aiming to contribute from a psychological lens by analyzing how these perceptions shape user acceptance. Collectively, these dimensions inform the central research question:

To what extent does AI literacy affect intentions of use and perceptions of generative AI tools?

Literature Review

This research is grounded in several key theoretical frameworks that illuminate the evolving relationship between AI and human behaviour in professional contexts. Central to this study is the concept of AI literacy, which serves as a foundation for understanding how individuals interact with and make sense of AI technologies in the workplace. AI literacy, as defined by Yi (2021, pp. 359-360), encompasses the ability to use, understand, and evaluate AI, and forms the backbone of this thesis's theoretical exploration.

This thesis draws upon two complementary sets of theoretical frameworks (see Table 1) to investigate the research question: *To what extent does AI literacy affect intentions of use and perceptions of generative AI tools?* First, technology acceptance theories - including the Technology Acceptance Model (TAM), Algorithm Aversion, and the Uncanny Valley - to explore perceptions of AI regarding its reliability, and the feelings it evokes that shape a user's stye of usage and trust. Second, it incorporates motivational and organizational psychology theories, specifically Vroom's Expectancy Theory and Self-Determination Theory (SDT), to understand how GenAI tools impact intrinsic motivation, and one's sense of agency. Together, these frameworks allow for the exploration of how AI literacy affects both a user's surface-level view (how users perceive and interact with AI) and their underlaying psychology (how those perceptions reinforce use).

Table 1.

Two Complementary Sets of Theoretical Frameworks.

	Theory	Core Idea	Application to GenAI in the Workplace	Relevance to Research Question
Technology Acceptance Theories	Technology Acceptance Model (TAM) (Davis, 1989)	User acceptance of technology depends on perceived usefulness and ease of use.	If workers don't find GenAI useful or easy to use, they are unlikely to adopt it - especially those with lower AI literacy.	Helps explain intention to use GenAI tools based on perceived utility and usability.
	Algorithm Aversion (Dietvorst et al., 2015)	People are less likely to trust algorithms after seeing them err - even when they outperform humans.	Workers may reject GenAI tools due to mistrust, especially when lacking literacy to interpret errors.	Explains how low AI literacy may increase scepticism or resistance to using GAI.
	Uncanny Valley (Mori, 1970; Wu, 2023)	Humans feel discomfort when technology is too humanlike.	GenAI like ChatGPT may trigger unease if its responses feel too "real," leading to lower acceptance.	Adds a psychological dimension to understanding perception and fear of AI.
Motivational and Organizational Psychology Theories	Vroom's Expectancy Theory (Vroom, 1964)	Motivation is a function of effort → performance → reward (expectancy, instrumentality, valence).	GenAI may disrupt this chain - workers feel their effort doesn't impact outcomes, lowering motivation.	Explains how perceived loss of contribution affects engagement and motivation.
	Self-Determination Theory (SDT) (Deci & Ryan, 2012)	Intrinsic motivation depends on meeting the needs for autonomy, competence, and relatedness.	GenAI can undermine these needs when users feel forced to use tools they don't understand.	Helps explain how lack of AI literacy threatens motivation and leads to AI "feels like cheating".

Note. Source: Own interpretation.

AI Literacy as a Socio-Technical Competency: Definitions, Foundations, and Subcomponents

Literacy is a foundational competency for individuals to navigate society and understand the essential skills of the era they live in (Yi, 2021, p.359). As Yi (2021, p. 359) explains, “While the ability to read and write was a basic social competency in the era of letters, the ability to use computers happens to be a basic competency in the era of computer development”. The same pattern is emerging in the current AI-driven era. AI literacy is a new form of basic competency - one that enables individuals to meaningfully participate in and adapt to the demands of modern society.

Many definitions of AI literacy have emerged and evolved over the past few years. Long and Magerko (2020, p. 2) frame AI literacy as a set of competencies enabling individuals to critically assess AI, communicate effectively with it, and apply it meaningfully in various life domains. Similarly, according to Yi (2021), AI literacy encompasses an individual's ability to use, understand, and evaluate AI tools. Yi (2021, pp. 360-363) also emphasizes the ability to forecast the consequences of AI use (ethical, practical, in relation to hiring or the environment), as well as the ability to engage in metacognitive reflection and anticipation (see Table 2). Further, deepening the focus on system-level understanding, Kreinsen and Schulz (2023, p.4) define AI literacy as the ability to explain how AI systems work, recognize their methods and limitations, and critically interpret and build upon their outputs. Collectively, the three definitions place critical understanding and reflective engagement at the core of AI literacy. Furthermore, they suggest that AI literacy is not a static skillset but a dynamic set of capabilities that requires individuals to understand AI tools, anticipate their impacts, and engage critically with them.

Table 2.

Interpretation of Use, Understanding and Evaluation.

AI literacy Competency	Description	Practical Example via ChatGPT	Underlying Sub-Competency
Use	The ability to interact meaningfully with AI systems to achieve goals.	Using ChatGPT to plan a trip by crafting prompts that anticipate needs such as budget, mobility, or tone.	Anticipation
Understand	Knowing how AI systems work and what potential limitations they have.	Understanding that ChatGPT is probabilistic, not sentient; realizing it may not “know” recent events or that it can “hallucinate” confident but false answers.	Anticipation
Evaluate	Critically reflecting on the quality and relevance of AI-generated outputs.	Asking whether an answer makes logical sense or might be hallucinated; engaging in metacognitive reflection to assess trustworthiness.	Metacognition + Data Literacy

Note. Source: Own interpretation.

Scholars continue to debate whether previously established literacies - such as technological literacy, data literacy, and digital literacy - serve as essential foundations for an individual to develop AI literacy. Interestingly, Kreinsen and Schulz (2023) introduce the concept of a “triad” - comprising of digital literacy, data literacy, and AI literacy - as a set of interrelated literacies that must be understood and developed in tandem (see Figure 1). They emphasize that these literacies are not isolated skill sets but instead overlap and reinforce one another (Kreinsen & Schulz, 2023, p. 3). Within this framework, data literacy is defined as the ability to understand what data is collected and why, along with the capacity to critically evaluate its origin, quality, and processing methods. Moreover, digital literacy refers to the ability to identify which technologies can be used, for what purposes, and to reflect on their opportunities, limitations, and relevance within a professional context (Kreinsen & Schulz, 2023, p. 4).

Figure 1.

The Triad of Digital Literacy, Data Literacy, and AI Literacy

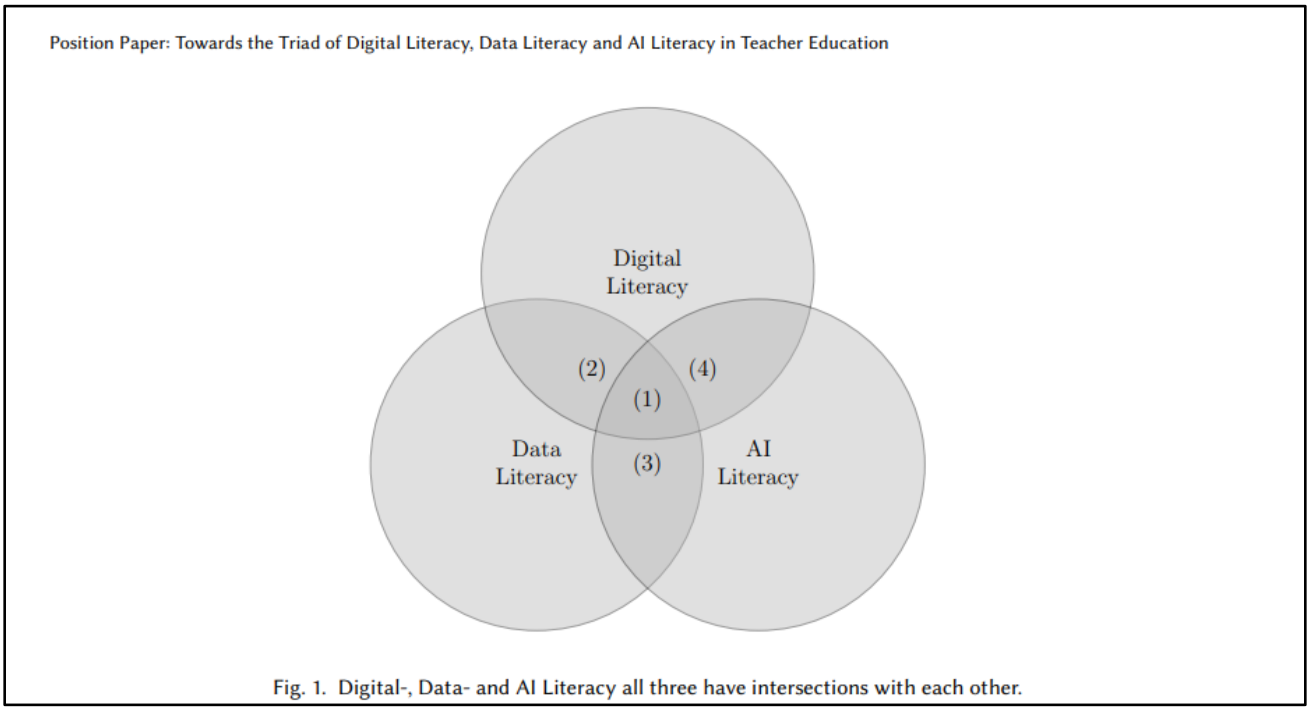


Fig. 1. Digital-, Data- and AI Literacy all three have intersections with each other.

Note. Source: Kreinsen & Schulz (2023, p. 3).

Mabrito and Medley (2008, p.1) also contribute to the discussion by distinguishing technological literacy from digital literacy. While the former concerns technical competence and tool use, the latter emphasizes the ability to communicate, navigate, and operate fluently in immersive digital environments. In contrast, Young and Pearson's (2002, p. 3) conceptualization of technological literacy is more elaborate and comprises three interdependent dimensions: knowledge, ways of thinking and acting, and capabilities. Knowledge involves an understanding of core technological concepts, and an awareness of the pervasive role technology plays in society. Ways of thinking and acting include the ability to critically assess the risks, benefits, and societal impacts of technology. Capabilities refer to practical skills such as troubleshooting everyday tools and applying quantitative reasoning (Young & Pearson, 2002, p. 4). Technologically literate individuals, as the authors explain, are more likely to make well-informed decisions when navigating new technologies (Young

& Pearson, 2002, p. 3). As established in the preceding sections, understanding the dominant technologies of one's era is essential for participation in society (Yi, 2021, p. 358).

A common consensus among scholars such as Yi (2021), Long and Magerko (2020) is that while data, technological, and digital literacy serve as important prerequisites for the development of AI literacy, they are not sufficient on their own. AI literacy extends beyond these foundations due to the unique nature of AI tools - tools that are not only complex and dynamic, but also capable of autonomous output generation and decision-shaping. This perspective is further validated by recent literature questioning the adequacy of traditional technology acceptance frameworks, such as the Technology Acceptance Model (TAM), in the context of AI (Koenig, 2024, p. 1336). The TAM, originally proposed by Davis (1989), provides a robust framework for understanding how users accept and use technology. According to TAM, perceived usefulness and ease of use are critical determinants of technology acceptance. However, AI's unique agent-like qualities complicate the simple user-tool dynamics posited by traditional TAM.

While TAM has long served as a reliable foundation for studying user interaction with technology, its framework proves insufficient when applied to AI systems with agent-like characteristics. As Koenig (2024, p. 1336) argues, AI's ability to act autonomously, delegate tasks, and affect individuals indirectly challenges the core premise of TAM, which assumes that technology lacks agent-like properties. This assumption falls short when applied to AI tools. These insights reinforce the idea that AI literacy is not simply an extension of digital or technological literacy, but a distinct capability shaped by a new class of technologies that fundamentally alter human-machine interactions.

As a result, AI literacy demands a more nuanced understanding of algorithmic logic and systemic limitations. It also requires the ability to critically evaluate AI outputs, reflect metacognitively on interactions with these systems, and anticipate their potential consequences (Ghazizadeh et al., 2012; Schepman & Rodway, 2020; Vorms & Combs, 2022). In response to critiques regarding TAM's limitations when applied to GenAI tools, Choung, David, and Ross (2023) developed an expanded version of the model that integrates trust as a multidimensional construct - introducing both functionality trust and human-like trust. This thesis further adapts and applies the framework proposed by Choung and colleagues (2023), as discussed in a subsequent, dedicated section.

Anticipation

A particularly relevant sub-component of AI literacy is anticipation. Its importance emerges through the concept of futures literacy - a capability emphasizing how perceptions of the future shape present behaviour (Miller, 2018, p. 15). Futures literacy enables individuals to identify, question, and revise their anticipatory assumptions, which are often unconscious expectations guiding their interactions with emerging technologies. The core competence acquired through futures literacy is anticipation - a foundational skill for navigating complex societal shifts and technological transformations.

Miller (2018, pp. 59-60) defines anticipation through three interrelated modes: optimization, contingency, and novelty. In the context of this study, optimization reflects the ability to craft highly detailed and tailored prompts for ChatGPT, including precise contextual information such as budget constraints, mobility needs, and activity preferences. Contingency involves the adaptation and critical adjustment of prompts in response to known limitations of GenAI - such as recognizing and compensating for hallucinations or outdated / misunderstood information. Finally, novelty emphasizes the user's capacity to recognize that the GAI's effectiveness is not fixed but can be dynamically shaped by the creativity and specificity of the prompts given. For example, "Can you create a story-driven trip where every site tells a part of a fictional narrative, like following a hidden mystery around Paris?". Through novelty, users move beyond conventional use cases to imagine new possibilities, creating a collaboration with AI systems. These elements; goal precision, constraint setting, specificity, model understanding, ambiguity mitigation, domain context, and verbosity control; form the basis for assessing the correct use of GenAI in this study. Their operationalization is elaborated on in the section Operationalization of Concepts.

Anticipation is seen as a central cognitive skill and human capability in Miller's (2018) work. They frame anticipation as a way to prepare for uncertainty by imagining how the present actions could play out in light of possible futures (p. 53). Yi (2021) aligns with this perspective, arguing that AI literacy must extend beyond technical proficiency to include metacognitive reflection and the capacity to anticipate outcomes in rapidly evolving environments. This anticipatory mindset encourages individuals to critically assess the societal implications of AI, and question default results.

Miller (2018) distinguishes between two primary modes of anticipation: Anticipation for the Future (AfF), which focuses on planning and optimization, and Anticipation for Emergence (AfE), which supports reframing and innovation. Both forms align with the goals of AI literacy by fostering scenario awareness, critical thinking, and adaptive learning. In the workplace, this translates to an employee's ability to use GenAI tools like ChatGPT effectively by anticipating their limitations, implications, and evolving roles within organizational workflows. This workplace application of anticipation directly aligns with earlier definitions of AI literacy provided by Long and Magerko (2020) and Yi (2021), both of whom emphasize the importance of critical thinking, adaptability, and reflective use of AI tools.

When examined through the lens of anticipation, the overarching research question - *"To what extent does AI literacy affect intentions of use and perceptions of generative AI tools?"*- gains additional depth. Anticipation enables individuals to mentally simulate future scenarios, assess potential outcomes, and make informed decisions in real time. An AI-literate individual with strong anticipatory skills is more likely to engage meaningfully with GenAI tools, recognize their limitations, and use them strategically. This suggests that anticipation, as a subcomponent of AI literacy, may play a key role in shaping both intentions of use and perceptions of usefulness or trustworthiness. Conversely, those who lack anticipatory competence may struggle to prompt effectively, leading to frustration, mistrust, and eventual disengagement from tools like ChatGPT. From the previous stems the creation of H1a detailed below.

Metacognition

Commonly defined as "thinking about one's thinking," *metacognition* is a core competency of AI literacy (Yi, 2021, p. 362). While anticipation prepares users to imagine and safeguard future outcomes, metacognition anchors them in the present by enabling reflection on their thinking process in real time. It empowers individuals to evaluate the clarity of their prompts (e.g., *Why am I using these words?*), question the relevance of AI responses (e.g., *Why did the GenAI respond this way? What assumptions is it making?*) and assess whether those responses align with their goals. Through this kind of reflective loop, users shift from passive recipients of AI output to active, critical collaborators.

Yi (2021, p. 363) emphasizes that metacognition is especially important in AI interactions because it enables users to not only *react* to machine output but also *learn* from it - an essential skill for long-term adaptation and digital confidence. In addition to reacting and learning, metacognition seems to also allow for an individual to re-gain control over the direction of the GenAI 's output. From this perspective, metacognition is a critical capability for AI-literate individuals, as it supports the ongoing evaluation of both their own cognitive processes and the AI's performance. As Yi (2021) notes, it allows users to "check the quality of the learning data" the GenAI system was trained on - referring not only to its foundational datasets but also to each individual user's prompts. This collaborative and reflective human-AI relationship allows for active use of AI and perhaps contributes to acceptance and trust of GenAI tools. The previous contributes to H1 (AI's workplace acceptance), which will also be addressed in a following section.

H1: Higher levels of AI literacy are positively associated with the acceptance of generative AI technologies in the workplace.

- **H1a:** Higher levels of *anticipation* are positively associated with the acceptance of generative AI technologies.

- **H1b:** Higher levels of *metacognition* are positively associated with the acceptance of generative AI technologies.

This thesis positions metacognition as a critical cognitive skill for safeguarding users against GenAI bias. Cohran (2025, p. 22) discusses GenAI "hallucinations"; where GenAI models produce seemingly realistic syllogisms, that are not justified by their training data, but fit the theme of discussion. These *hallucinations* may appear plausible but are often inaccurate and pose serious risks to credibility, ethical judgment, and decision-making quality. A critical function of metacognition in AI literacy lies in its potential to protect users from the inherent biases and hallucinations of GenAI systems. By fostering metacognitive awareness, such as pausing to question the relevance and accuracy of an AI output, users can recognize and mitigate these risks.

There is a strong conceptual link between metacognition and data literacy. As Kreinsen and Schulz (2023, p. 4) note, data literacy includes the ability to critically evaluate a dataset's origin, quality, and processing methods. Both competencies encourage reflective engagement, enabling users to detect flawed or biased content. In this way, metacognition, and data literacy function as cognitive safety nets within AI environments. This suggests that where metacognition is present, data literacy may also be active and further, the relationship implies that digital and data literacy form critical prerequisites for individuals to develop true AI literacy.

However, recent findings by Fernandes et al. (2024) offer a cautionary perspective. While users' task performance improved with AI support, their metacognitive monitoring often declined - particularly among those with higher AI literacy. Their participants also reported greater confidence in their outputs without corresponding improvements in accuracy, revealing a disconnect between perceived and actual performance. Fernandes et al. (2024, p. 11) describe this as "AI cancelling the Dunning-Kruger effect," a cognitive bias where low-competence individuals overestimate their abilities and high-competence individuals underestimate them. The researchers found that the cognitive support provided by AI seemed to mask a lack of deep understanding, suggesting that higher technical proficiency does not always translate into more reflective or accurate self-evaluation. Fernandes et al. (2024) attribute this phenomenon to overconfidence and blind trust in AI - even among otherwise proficient users.

One particular finding from Fernandes et al. (2024) stands out: users with higher AI literacy experienced improved task performance *but simultaneously showed a decline in metacognitive monitoring*. This creates a paradox: how can one be considered AI literate without actively engaging in metacognitive reflection? If task performance improves in the absence of such reflection, can it truly be seen as evidence of correct use of (generative) AI (i.e., high task performance)? These findings reveal a potential limitation in the conceptualization of AI literacy, which tends to emphasize functional or technical proficiency while neglecting deeper cognitive engagement. Users may appear to interact with AI "correctly", yet still fall into cognitive traps such as overconfidence or blind trust, indicating lower levels of AI literacy.

This thesis contributes by arguing that true AI literacy must include metacognitive reflection and anticipatory reasoning, both of which shape a user's ability to evaluate, adapt, and guide AI outputs effectively. In this context, *correct use* is not simply defined by task completion or surface-level interaction, but by the quality of engagement with the AI system. This argument is supported by Ekin's (2023) work, which identifies core features of high-quality prompts (e.g. goal precision, and awareness of the model's limitations) as indicators of meaningful human–AI communication. Upon closer inspection, these features implicitly require the user to activate both metacognition and anticipation. By integrating insights from Fernandes et al. (2024) and Ekin (2023), this thesis proposes the following hypothesis:

H2: Higher levels of AI literacy are positively associated with the correct use of generative AI technologies.

As this thesis contributes to the conceptual development of AI literacy by integrating metacognition and anticipation as higher-order cognitive processes, this hypothesis enables a closer examination of whether users who demonstrate both technical proficiency and reflective cognition are more likely to use GenAI tools effectively - beyond surface-level success.

An alternative or complementary interpretation of Fernandes et al.'s (2024) findings is that inaccurate self-evaluations may not stem solely from overconfidence or blind trust, but from a deeper psychological disconnect. Users who feel that the AI carried out the majority of the cognitive work may struggle to take full ownership of the output. This dynamic aligns with Vroom's Expectancy Theory (Vroom, 1964), explored in detail later in this thesis, which discusses how motivation hinges on three beliefs: that effort leads to performance, performance leads to outcomes, and that those outcomes are personally valued.

When users feel detached from the process ("It wasn't really me who solved it"), yet simultaneously trust the tool's output ("How could the robot get it wrong?"), their self-assessments became distorted. Fernandes and colleagues (2024) found that AI use inflated confidence levels even when task performance did not improve. This finding stands in contrast to theories such as algorithm aversion (Dietvorst et al., 2015), which predict scepticism and reduced trust in AI-generated outputs. Instead, Fernandes et al.'s participants - who were noted to possess relatively high levels of AI literacy - appeared to advocate for the tool's reliability through their self-reported confidence.

Ironically, this surface-level proficiency may undermine metacognitive precision and reinforce a misleading sense of competence. While individuals may appear to use GenAI "correctly" to complete a task, they are not truly AI literate if they lack the metacognitive capabilities required for critical, reflective engagement. Intriguingly, the overconfident users observed by Fernandes et al. (2024) did not exhibit fear or scepticism toward the AI - in fact, they placed a high degree of trust in it, to the point of relying on the tool for their own self-assessments. This stands in contrast to a growing body of research that highlights how fear, mistrust, and even subtle forms of xenophobia continue to shape human - AI relationships. The next section explores these emotional and psychological barriers in greater depth.

Trust, Fear, and Xenophobia

While many definitions of AI literacy emphasize technical skills such as understanding, using, and evaluating AI systems, psychological and emotional factors also play a critical role in shaping how individuals perceive and engage with these tools. In particular, *trust*, *fear*, and *xenophobia* are increasingly recognized as influential factors in the acceptance and effective use of GenAI. These psychological responses are not only shaped by individual perceptions but are often reinforced through sociocultural dynamics - such as shared anxieties, speculative narratives, and public discourse surrounding machines performing human-like tasks, algorithmic bias, deepfakes, and data privacy concerns (Kong et al., 2021; Hong, 2021). As previously discussed, AI literacy encompasses not only technical competence but also higher-order cognitive processes like metacognition and anticipation. This section builds on that foundation by exploring how emotional and social responses - especially those rooted in uncertainty, unfamiliarity, and lack of understanding - further influence AI literacy, particularly in relation to trust and adoption in professional settings.

This thesis defines trust as a user's willingness to rely on AI systems - exemplified by Fernandes et al.'s (2024) participants, as discussed in the previous section. Fear, by contrast, encompasses anxieties about AI's potential to displace human roles or undermine individual agency. As a subcategory of fear, xenophobia, in this context, goes beyond cultural or national prejudice and takes on a technological dimension - an instinctive resistance or discomfort toward AI-generated content because it feels "foreign". Technological xenophobia is especially relevant in discussions around GenAI; a relatively new and often poorly understood tool (Hong, 2021, p. 1024). This sense of discomfort often stems from both the unfamiliarity of the technology and a lack of understanding about how it works. Where understanding is absent, mistrust can grow - leading to feelings of suspicion or the perception that something is *strange*. This creates an unsettling ambiguity around GenAI systems that (seem to) imitate human traits without actually being human. To elaborate, large language models like ChatGPT, for example, are trained on vast datasets composed of human-created text. As a result, their outputs often mirror human language patterns. It is precisely this humanlike appearance without human essence that can evoke discomfort, reinforcing the psychological distance and resistance encapsulated by technological xenophobia.

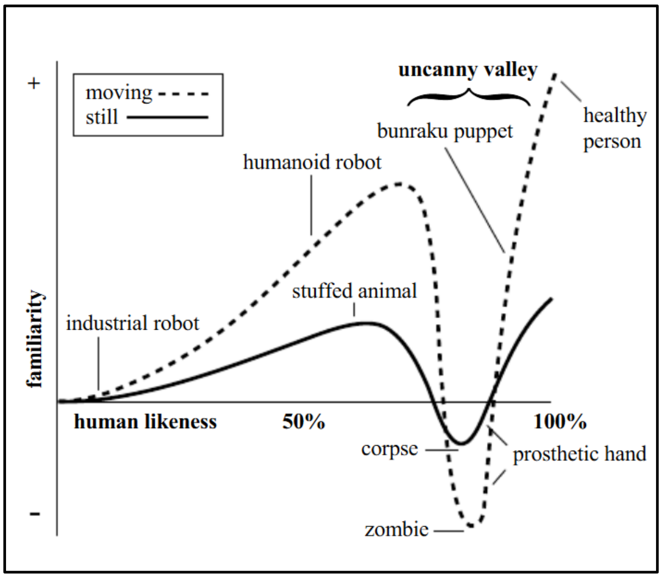
Xenophobia and The Uncanny Valley. The research of Hong (2021, p. 1029) further complicates our understanding of human - AI interaction by revealing that machine-distinctive performances are preferred over human-like ones. Contrasting with Fernandes et al.'s (2024) participants - who embraced AI and were willing to align themselves with its results - Hong's (2021) study points to a more cautious behavioural pattern: a preference for AI that "stays in its lane". In this case, users favoured tools that were clearly artificial and non-sentient, even at the expense of technological sophistication. This reveals a deeper psychological dynamic - a subtle "us vs. them" mentality; where "them" would be AI - in which users feel more comfortable with systems that do not blur the line between human and machine. Keeping these boundaries intact helps users avoid discomfort, perceived threat, or role confusion, creating a xenophobic atmosphere towards human-like behaviours by AI or robots. Hong (2021, p. 1028) attributes these reactions to expectancy violations, i.e. instances where AI behaves outside anticipated norms, which significantly impact users' willingness to engage with such systems.

Hong's findings are closely aligned with the theory of algorithm aversion (Dietvorst et al., 2015), which found that users' trust in algorithms quickly declines after witnessing errors - even when those systems outperform humans on average. While algorithm aversion is typically triggered by observable errors, Hong's (2021) concept of expectancy violations refers more broadly to AI behaviour that deviates from anticipated norms and acts "human like". In both cases, users demonstrate a low tolerance for unpredictability in technological systems, reinforcing the idea that even subtle deviations from expectation can evoke discomfort or rejection. This sensitivity to deviation likely underpins phenomena such as the Uncanny Valley and technological xenophobia.

Hong's (2021) findings (i.e. a preference for AI that "stays in its lane") is closely connected to the Uncanny Valley theory originally proposed by Mori (1970), which suggests that as artificial entities become increasingly humanlike in appearance or behaviour, they may evoke unease, discomfort, and a sense of eeriness. According to Mori (1970), people generally respond more positively to machines that appear progressively human (i.e. four limbs, two eyes) - up to a critical threshold (see Figure 2 - left). Beyond this point, figures that look and act almost, *but not quite*, human can trigger discomfort. Subtle mismatches between expectation and reality - such as unnatural skin texture, limited responsiveness, or a lack of emotional expression - become unsettling, plunging the observer into what Mori (1970) termed the "uncanny valley" (see Figure 3 - right). One example is a prosthetic hand that looks human but feels cold and lifeless; its realism violates the expected signs of vitality, thereby provoking unease, discomfort and thus the "uncanny valley" effect (Mori, 1970).

***Figure 2*.**

Image on Left - From Mori (1970). Bukimi no tani [The uncanny valley]



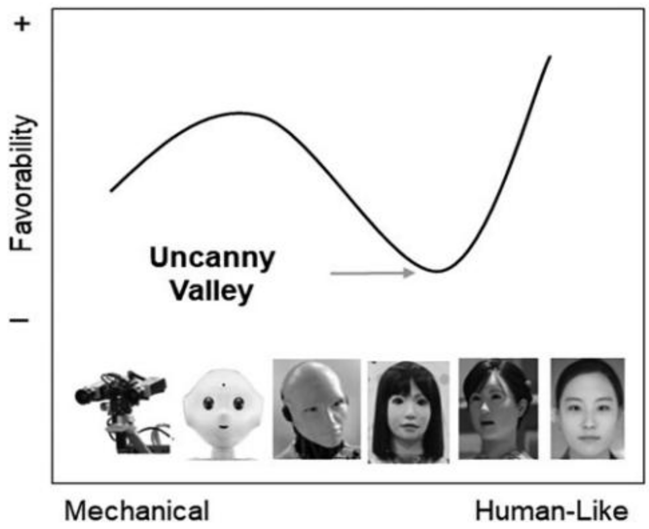


Figure 3.

Image on Right - From Jung, Cho, and Kim (2021). Illustration of the Uncanny Valley with Examples of Humanoid Robot Faces.

Wu (2023, pp. 4-5) extends Mori’s (1970) Uncanny Valley theory beyond humanoid robots to include AI-generated content, arguing that digital outputs that closely mimic human traits can also provoke discomfort. Wu’s (2023) study provides statistically significant evidence of the “social uncanny valley” - a phenomenon where human-like AI outputs increase feelings of eeriness and unease. Notably, Wu (2023, p. 35) found that participants reported a stronger sense of competition toward human-like AI products than toward those created by other humans. These emotional reactions may lead to increased hostility and resistance, particularly in workplace contexts where users perceive AI (content) as a threat to their roles (Wu, 2023, p. 70).

Ultimately, the findings of Hong (2021) and Wu (2023) suggest a clear preference for AI that complements rather than competes with human capabilities - even when the technology itself may offer superior performance. This reinforces a psychological need for AI to remain within its expected assistive scope, supporting the Uncanny Valley theory. The desire to maintain clear boundaries between humans and machines reflects an underlying “us vs. them” mentality - a core feature of technological xenophobia. While the Uncanny Valley describes the emotional unease triggered by almost-human AI, technological xenophobia captures a deeper, bias-driven resistance to engaging with such systems that feel *foreign*. This resistance often manifests as avoidance, mistrust, or outright rejection. In this way, xenophobia can be seen as an affective outcome of the perceptual discomfort introduced by the Uncanny Valley. As noted earlier, xenophobia in this context is not cultural but cognitive - rooted in an instinctive resistance toward AI-generated outputs that feel human-like yet are not human.

Here, AI literacy plays a critical role in reducing xenophobia. When individuals lack understanding of how GenAI systems operate, they are more likely to interpret their outputs as strange, and even, feel threatened, prompting emotional resistance. However, when users build literacy, they acquire the conceptual tools to demystify these systems: understanding their limitations, recognizing their training processes (and thus why they feel “almost human”) and anticipating their behaviours. In this sense, AI literacy offers technical and emotional competence that reduces xenophobia. This dynamic - where understanding replaces uncertainty and reduces fear - forms the basis for the following hypothesis:

H3: Xenophobia mediates the relationship between AI literacy and acceptance of AI technologies, such that higher AI literacy reduces xenophobia, thereby increasing acceptance.

(Mis)trust. Alongside xenophobia, another psychological dimension that significantly influences the use and perception of GenAI tools is trust. While both constructs are partly rooted in uncertainty and limited understanding of these systems, they manifest differently: xenophobia emerges as a fear-based rejection of the unfamiliar, whereas trust in technology is shaped by users' perceptions of its usefulness, reliability, and transparency (Davis, 1989).

A foundational concept under the umbrella of trust in technology and specifically GenAI, is algorithm aversion. As explored by Dietvorst and colleagues (2015), algorithm aversion describes users' reluctance to trust or rely on algorithmic systems even when they consistently outperform human judgment. Notably, empirical evidence shows that exposure to algorithmic errors can rapidly erode user trust, despite the algorithm's overall predictive accuracy. Given the existing reluctance to trust simpler, rule-based systems, like evidence-based forecasting tools, it can be expected that trusting more complex, GenAI systems would pose even greater challenges.

In this context, AI literacy plays a pivotal role in shaping the relationship between trust and technology. Individuals with higher levels of AI literacy are better equipped to understand how GenAI systems operate, including their probabilistic outputs, learning mechanisms, and inherent limitations. This thesis conceptualizes AI literacy as building upon digital and data literacy (see Figure 4), aligning with perspectives raised by Yi (2021), Kreinsen and Schulz (2023), and Long and Magerko (2020). Accordingly, individuals who possess the needed technical competencies and the ability to critically evaluate a dataset's origin, quality, and processing methods are more likely to form realistic expectations about when and how to trust GenAI. This informed understanding enables them to interpret occasional system errors without disproportionately losing trust in the technology. Ideally, AI-literate users can even anticipate and prevent such errors before they occur. As a result, these individuals are more likely to perceive GenAI systems as competent and reliable - within reason - thus strengthening trust and increasing their willingness to use such tools. As Choung and colleagues (2023) emphasize, trust is essential for AI acceptance. Their findings show that trust significantly influences users' attitudes and behaviors toward GenAI, with a direct effect on intention to use, mediated by perceived usefulness and overall attitude.

These insights inform the following hypothesis, which investigates the mediating role of trust in the relationship between AI literacy and the acceptance of GenAI technologies:

H4: Trust mediates the relationship between AI literacy and the acceptance of generative AI technologies in the workplace, such that higher AI literacy leads to higher trust, which in turn increases acceptance.

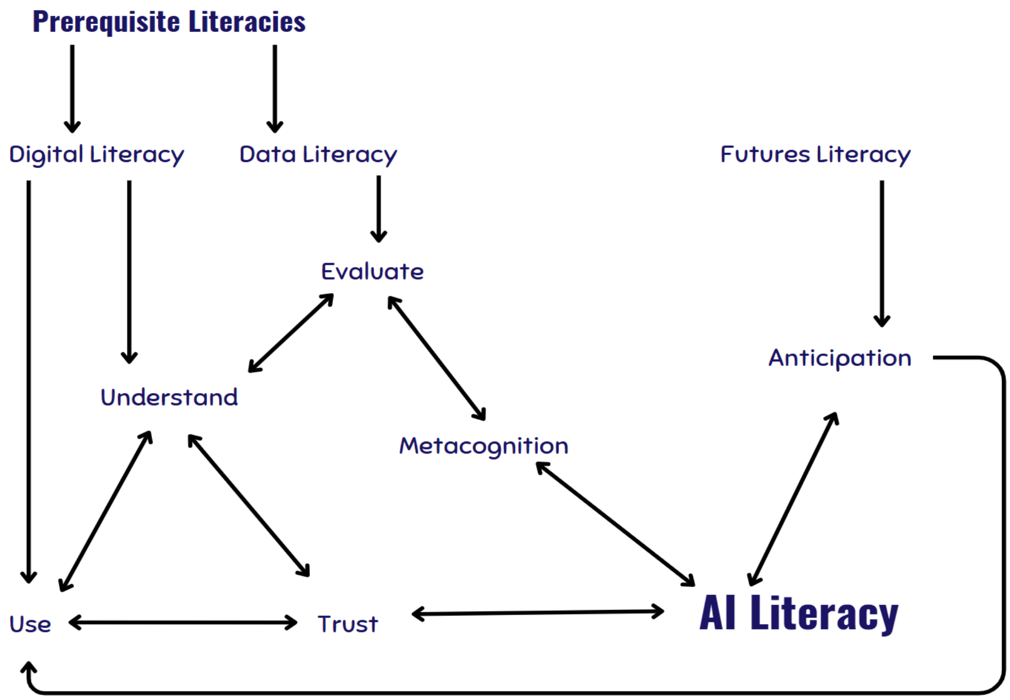
Conceptualizing AI Literacy: A Visual Synthesis

To consolidate the theoretical insights outlined in this literature review so far, the following diagram (Figure 4) offers a visual synthesis of how AI literacy develops through foundational literacies, cognitive sub-skills, and behavioural feedback mechanisms. Drawing from the conceptual models and reviews of Yi (2021), Kreinsen and Schulz (2023), and Long and Magerko (2020), this model illustrates how *digital literacy* and *data literacy* serve as prerequisite competencies, while *futures literacy* supports the development of a higher-order capability: *anticipation*. *Metacognition* is shown to stem from *data literacy,* specifically through the process of *evaluation*.

Importantly, *use* is portrayed as a layered behaviour, as users may interact with GenAI tools without necessarily possessing AI literacy. For this reason, *anticipation* is linked directly to *use*, illustrating how critical foresight can transform basic interaction into literate engagement. Additionally, *use* is connected to *trust* to reflect an experiential learning path - namely, "the more I use, the more I understand, and the more I know when and how to trust". Finally, AI literacy is conceptualized both as an outcome and a feedback loop: the double-headed arrows indicate that increased AI literacy leads to more effective use, primarily through *trust* grounded in *model understanding,* which in turn further reinforces literacy. In other words, the more individuals understand and skilfully engage with GenAI tools, the more they continue to strengthen their *metacognition*, *anticipation*, and *trust* over time. These developments, in turn, contribute to increased AI literacy.

Figure 4.

Components and Developmental Flow of AI Literacy.



Note. Source: Own interpretation.

Acceptance of GenAI in The Workplace: Motivation, Displacement, and The "Cheating" Perception

Beyond contributing to the conceptualization of AI literacy, this thesis also aims to provide practical insights into how GenAI is experienced in workplace settings - particularly in relation to employee needs. As GenAI tools become increasingly integrated into professional environments, it is essential to examine their impact on employee motivation and the emergence of emotional discomfort. To this end, the following section draws from organizational psychology theories to explore the factors that influence employee acceptance of GenAI. Specifically, it considers how emerging human-AI dynamics may challenge long-standing psychological models of motivation. This is especially relevant in organizations where technology is implemented through top-down decision-making. In such contexts, the introduction of GenAI without adequate training or support can significantly reduce employee agency (Cohran, 2025; Walkowiak, 2023).

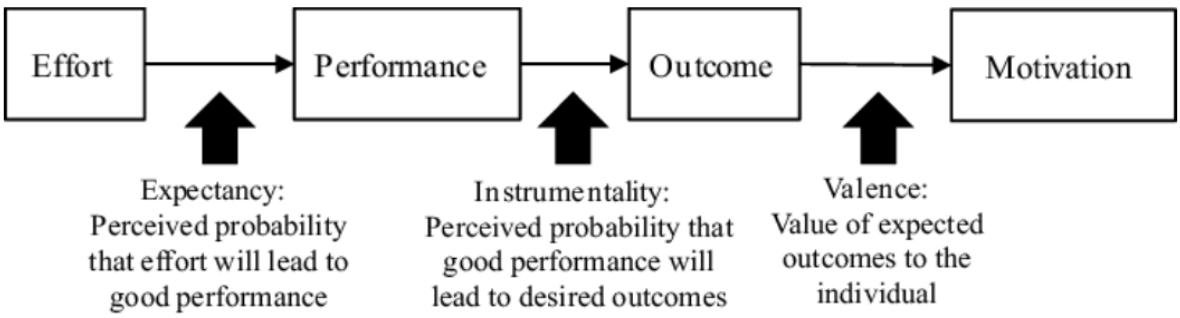
A concerning trend in the development of GenAI tools is the evident structural bias toward replacing human labour rather than amplifying it (Cohran, 2025, p. 16). Cohran (2025, p. 16) notes that this tendency is intensified by the time pressures associated with bringing AI products to market - where release speed often overrides user-centred needs and neglects the long-term implications of excluding the worker's perspective. As a result, many employees are left to interact with tools that make them feel displaced, diminishing their sense of contribution and lowering their intrinsic motivation; thus, reinforcing the feeling of being replaced by GenAI (Cohran, 2025, p. 16 - 25). This displacement and diminished agency can lead to negative perceptions of GenAI and, accordingly, reduced acceptance in the workplace. This reasoning is derived from the TAM, by Davis (1989), which states that user acceptance of new technologies is largely driven by perceived usefulness. If GenAI is viewed as a threat rather than a supportive tool, its perceived usefulness diminishes - undermining acceptance. Given these dynamics, strengthening AI literacy may serve as a critical intervention, helping individuals reframe AI as an empowering tool rather than a threat. The above syllogism (also) contributes to the exploration of H1, which examines how AI literacy shapes GenAI's acceptance. As noted earlier, acceptance of GenAI is operationalized via the extended TAM, by Choung, and colleagues (2023); details on this are in a relevant subsequent section.

Human-centred organizational theories, particularly Vroom's Expectancy Theory (Vroom, 1964) and Self-Determination Theory (Deci & Ryan, 2012) can provide insights into the psychological phenomena of feeling replaced or devalued by GenAI's workplace integration. Vroom's Expectancy Theory (illustrated in figure 5) posits that an individual's motivation hinges on three core beliefs:1) effort leads to performance (expectancy), 2) that performance leads to outcomes (instrumentality), and 3) that these outcomes are personally valued (valence). This model has long served as the dominant framework for understanding (workplace) motivation. In the context of (generative) AI, all three components are disrupted. When workers feel that AI systems are doing the cognitive heavy lifting, their perceived control over outcomes weakens, lowering expectancy. If the final product is attributed to the tool rather than the individual, the connection between performance and reward is compromised, negatively affecting instrumentality. Finally, if the end result feels detached from personal effort, the reward carries little meaning - reducing valence.

In parallel to Vroom's breakdown of motivation, Self-Determination Theory (SDT) offers further insight into how GenAI can be emotionally and psychologically disruptive (Deci & Ryan, 2012). According to SDT, intrinsic motivation depends on the satisfaction of three universal psychological needs: autonomy (having control over one's actions), competence (feeling capable and effective), and relatedness (feeling connected to others). When employees are required to use AI tools they do not fully understand (undermining competence), are given no say in how the tools are implemented (limiting autonomy) or lack adequate peer or managerial support (reducing relatedness), they are more likely to experience *controlled motivation* - a state of doing something because they *have to*, not because they want to. This shift diminishes engagement and can increase resistance towards the adoption or effective use of GenAI in the workplace. In combination, Vroom's Expectancy Theory and SDT provide a long-standing and validated foundation for examining how GenAI tools may erode workplace motivation. Vroom's model suggests that motivation arises when individuals believe their effort leads to performance, performance leads to outcomes, and those outcomes are personally valued. SDT complements this by emphasizing the importance of autonomy, competence, and relatedness as essential psychological needs that sustain intrinsic motivation.

Figure 5.

Vroom's Expectancy Theory.



Vroom's (1964) Expectancy Theory. (adapted from http://faculty.css.edu/dswenson/web/OB/VIEtheory.html)

When GenAI systems are introduced without proper integration or user preparedness, they can disrupt both theories. This disruption can foster a perceived loss of agency, in which individuals feel the GenAI tool - rather than themselves - is responsible for outcomes. For some, this causes no discomfort. As discussed previously, Fernandes and colleagues (2024) showed that some users feel comfortable aligning themselves with GenAI output. For others, this may evoke the sensation that using AI "feels like cheating": a morally uncomfortable shortcut that bypasses the satisfaction typically associated with personal effort.

Despite personal morals, employees are increasingly expected to use GenAI tools regardless of their individual level of AI literacy, and often without feeling adequately prepared, engaged, or empowered (Cohran, 2025, p. 16 - 25). This emotional friction may explain why AI-assisted work can feel inauthentic or unsatisfying. This line of reasoning leads to the following hypothesis:

H5: The perception that using GenAI "feels like cheating" is negatively associated with AI literacy, such that individuals with higher AI literacy are less likely to experience this perception.

Cohran (2025, p. 24) underscores a relevant concern: as GenAI systems become more advanced, fears increase that human expertise and critical thinking may become obsolete. This can lead individuals to feel that their contributions are no longer meaningful, since AI can seemingly perform the same tasks. This creates a cognitive paradox: using GenAI can feel like "cheating" because it reduces the need for active mental effort - yet not using these tools may feel inefficient or professionally irresponsible. When employees no longer feel like cognitive assets and lack a sense of trust or security, collaboration between humans and GenAI becomes strained. This dynamic can trigger a self-reinforcing cycle: fear of AI leads to avoidance, avoidance limits opportunities to build AI literacy, and this persistent lack of literacy further intensifies fear and resistance toward GenAI adoption. Cohran (2025, pp. 20-24) emphasizes that AI literacy can serve as a tool for empowerment – a central premise of this thesis. Individuals with higher AI literacy levels are more likely to see GenAI as a strategic asset rather than a threat. For these users, using GenAI is not perceived as cheating, but rather as a smart and effective way to brainstorm ideas and save time. With proper training and support, employees can build the confidence needed to both trust and effectively utilize GenAI tools.

Synergy Between GenAI and Workers

Walkowiak (2023) discusses how GenAI, and human workers should be seen as distinct but interdependent actors in the production of productivity. Their framework distinguishes between “open learning organizations,” where human-AI interactions are encouraged, and “closed learning organizations”, where AI is restricted or banned. In open learning environments, GenAI adoption results in productivity gains because both humans and AI systems co-learn and detect task-related errors more effectively (Walkowiak, 2023, pp. 2-3). However, in closed environments, this synergy is lost, leading to diminished productivity and greater systemic risks. Crucially, Walkowiak (2023) emphasizes that error detection is essential and that the quality of GenAI integration depends heavily on matching workers and AI appropriately. Finally, Walkowiak highlights that the *way* firms integrate AI - particularly the degree of user interaction, preparedness, and error management - ultimately determines the quality of productivity with GAI. A similar sentiment is shared in Cohran’s (2025, p. 20) work, which notes that without proper education and support, employees may experience discomfort, confusion, or even ethical unease (as also discussed above) when interacting with AI tools.

The main argument emerging from this discussion is that AI literacy is essential for utilizing GenAI effectively. Without proper organizational onboarding and training, significant risks may arise (e.g. productivity loss, errors, and employee disengagement). When individuals can utilize the technology effectively, it creates an environment where societal concerns and psychological discomfort associated with AI interactions can be mitigated. Thus, understanding and enhancing AI literacy becomes crucial for navigating the complex interplay between humans and GenAI, fostering a more accepting and effective use of AI technologies in the workplace. As Yi (2021, p. 358) mentions, the ultimate purpose of literacy education is to provide individuals with the subjectivity and critical awareness necessary to navigate the basic media that shape society.

An Overview of All Hypotheses

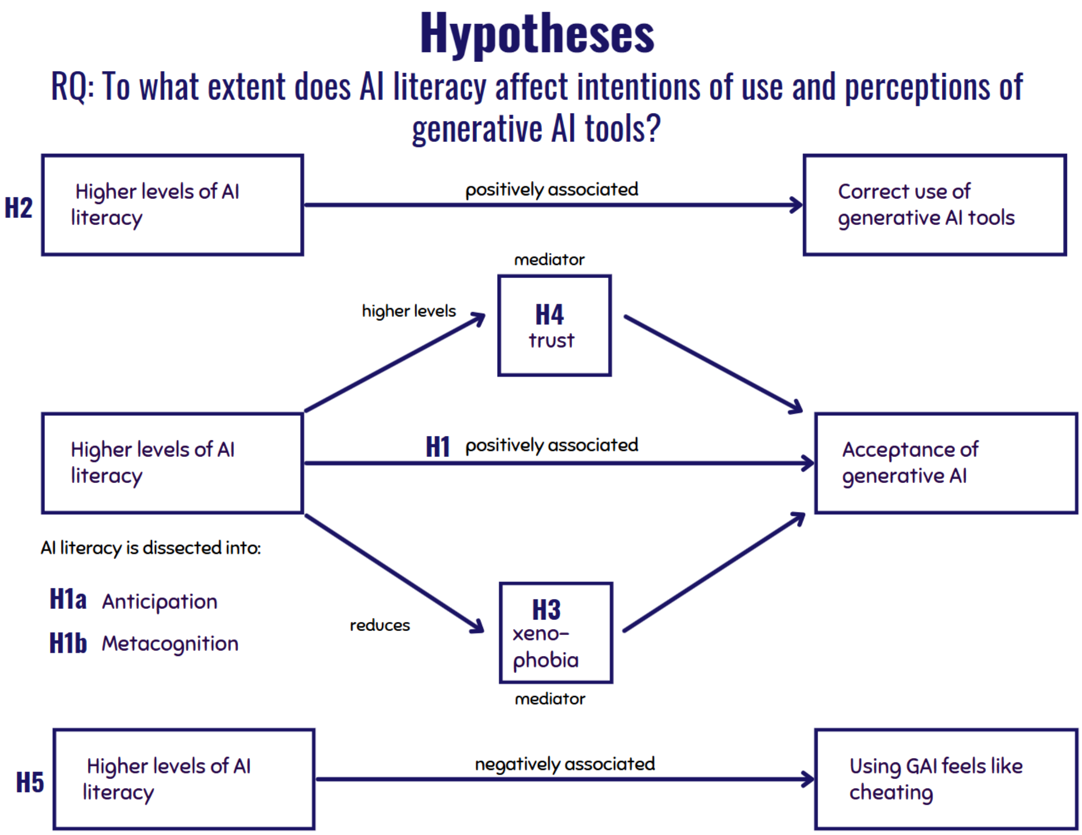
Before proceeding to the next section on research design and justification of methods, an overview of the study’s hypotheses is presented in Figure 6. As discussed, this thesis investigates the research question: *To what extent does AI literacy affect intentions of use and* *perceptions of GenAI?* A multi-path model is proposed, grounded in an expanded conceptualization of AI literacy that incorporates metacognition and anticipation, alongside psychological and technology acceptance factors.

The model begins by positing that higher levels of AI literacy positively influence GenAI acceptance (H1) and promote correct use of GenAI tools (H2). Further, two mediation effects are tested: trust (H4) and xenophobia (H3) are modeled as mechanisms through which AI literacy impacts GenAI acceptance. Finally, the model proposes that higher AI literacy is negatively associated with the perception that using GenAI "feels like cheating" (H5), addressing emerging concerns around moral discomfort.

Together, these hypotheses provide a comprehensive framework for understanding how literacy, cognition, and emotion influence workplace adaptation to GenAI tools.

Figure 6.

All Hypothesis



Note. Source: Own interpretation.

Research Design and Justification of Methods

This study employs a quasi-experimental design to comprehensively explore how AI literacy impacts both the correct use and acceptance of GenAI technologies like ChatGPT in (workplace) contexts. A quasi-experiment is particularly appropriate because it enables the investigation of naturally occurring differences in AI literacy among participants. AI literacy is an independent variable that cannot be easily, practically, or ethically manipulated. As such, participants will be asked to complete a vignette-based task: planning a trip for a fictional friend using ChatGPT and fill in various self-reported questionnaires.

This mixed-methods design generated both quantitative and qualitative data. Quantitative data was collected through validated self-report scales, including the AI Literacy Scale (AILS), the updated version of the TAM by Choung, and colleagues (2023) and an adapted version of the Negative Attitudes Toward Robots Scale (NARS). These were analysed in IBM SPSS Statistics using descriptive statistics, reliability testing, and exploratory factor analysis where applicable. Complementing this, Qualitative data was derived from participants' task-based prompt submissions, which were evaluated using a structured rubric and analysed thematically with a codebook, supported by ChatGPT. This dual approach enabled a comprehensive analysis of both measurable attitudes and real-world prompting behaviours.

This combination of structured task, self-reported measures, and behavioural analysis directly supports the study's central research question: *To what extent does AI literacy affect intentions of use and perceptions of generative AI tools?* By capturing both behavioural and attitudinal dimensions of interaction, the chosen method offers a rich and multidimensional understanding of how AI literacy functions in practice.

Participant Recruitment and Sampling Strategy

The study focuses on Generation Z (born between 1995 and 2012), specifically those aged 18 and above (born in or before 2004), to ensure ethical compliance (Park, Yourell, McAlister, & Huberty, 2023). The focus on Gen Z is multifaceted; as also discussed in the societal relevance section of this thesis; they are both the current up-and-coming work generation with a unique digital nativity that will potentially cause significant workplace impact. It was difficult to separate the Gen Z demographic from younger millennials but regardless, both demographics interaction with GenAI tools offer important insights into the role of literacy in shaping adoption and trust.

Participants were recruited using a multi-platform digital strategy tailored to reach members of Gen Z, while not explicitly excluding other demographics. Recruitment materials included Instagram stories and posts, LinkedIn posts, and messages shared across various group chats. A series of short promotional videos were created for social media outreach to encourage participation. The videos were used across approximately ten social media posts, accompanied by captions such as: *"Ever wonder how well you actually communicate with #ChatGPT? - Meet my AI avatar - here to tell you your AI prompting score. Take the AI Literacy Survey now → https://lnkd.in/daqw5R3X"* and *"Last day to get your AI score!"*

The messaging was deliberately people-centric, focusing on user curiosity and empowerment. By framing the study as an opportunity to receive personalized feedback in the form of an "AI prompting score", the outreach aimed to increase engagement and participation from digitally native users and provide an incentive to complete the survey.

Although the initial sampling strategy included platforms such as SurveySwap, this method yielded no responses. To supplement recruitment, the study employed Prolific, a participant-sourcing platform widely used in academic research. Approximately 40 respondents were recruited through Prolific and were compensated in accordance with the platform's fair payment guidelines.

In total, 95 participants completed the study. All participation was voluntary, and recruitment materials clearly emphasized that participants could withdraw at any time. This combination of organic and paid recruitment ensured a demographically relevant sample while balancing authenticity with sufficient data volume for analysis. Given the reliance on readily accessible participants, the sampling strategy used in this thesis can be classified as convenience sampling, which ensured timely data collection. While not representative of the broader population, the sample was sufficient for exploratory statistical analysis and offered preliminary insights into the needs and attitudes of the current and upcoming working generations.

Data Preparation and A Priori Criteria

The original dataset consisted of *N* = 95 participants. A response-time filter was applied to remove inattentive responses. Participants who completed the survey in less than 223 seconds (40% of the sample median of 556 seconds) were excluded. The final analytic sample included *N* = 86 valid cases.

Regarding gender, 48.9% identified as female, 43.3% as male, 2.2% as non-binary, 2.2% preferred to self-describe, and 3.3% preferred not to disclose. In terms of age, 33.3% were between 18-24 years, 52.2% between 25-34, and 14.5% were 35-64. While the study primarily targets Gen Z participants (ages 18-28), the age brackets followed standard survey conventions. Thus, limiting the ability to isolate older Gen Z respondents (ages 25-28), who were grouped with younger Millennials (ages 29-34) in the 25-34 bracket. Though the target population was Gen Z (18-28), survey conventions grouped ages 25-34 together. To address this, results are interpreted with attention to both the 18-24 and 25-34 brackets to capture generational dynamics.

In addition to demographic data, participants answered two background questions to contextualize their familiarity with GenAI tools. First, 92.6% (N = 91) reported having used at least one tool such as ChatGPT, Bing AI, or Google Gemini. Second, participants were asked to provide information about whether the use of such tools was permitted in their workplace or educational setting. Notably, 36.4% reported some form of restriction - either stating that use was prohibited, not really allowed, or that no explicit permission had been given. In contrast, 46.6% reported they were allowed to use GenAI, and 17.0% said its use was encouraged.

Operationalization of Concepts

This study distinguishes between two core approaches to measuring participants' AI literacy: an objective, performance-based evaluation, and a subjective, self-reported assessment. The first approach focuses on participants' ability to craft effective prompts for GenAI systems - referred to in this study as *correct use*. The second approach assesses perceived competence and attitudes toward GenAI through validated self-report scales. These dual methods enable triangulation between demonstrated skill and subjective perception. In addition, the self-reported measures provide insight into participants' (workplace) acceptance of GenAI and the psychological dimensions that may influence literacy and adoption.

The following sections outline the procedures used to operationalize these two approaches. Section 3.2.1 explains the process of establishing the benchmark criteria for high-quality prompts, as well as the development of the codebook used to score participants' prompt quality. Section 3.2.2 details the adaptation and evaluation of self-report instruments, including scales related to technology acceptance (e.g., TAM) and psychological responses such as xenophobia. For a concise overview of all key constructs, their corresponding measurement tools, and the hypotheses they are intended to test, see Table 6 at the end of this section.

Performance-Based Operationalization: Correct Use of GenAI

Participants' correct use of GenAI was assessed through a performance-based task that required them to construct a prompt for a travel planning scenario. A benchmark prompt was developed to represent high-quality GenAI use, incorporating specific elements that support effective human-AI communication. This included features such as constraint-setting, and goal precision.

To develop the benchmark, the study combined insights from both front-end, user-centered prompt engineering strategies (e.g., clarity, constraint-setting, goal precision) and back-end, system-centered considerations (e.g., how ChatGPT interprets task structure and context). These perspectives informed the creation of a custom prompt evaluation rubric (see Table 3: Codebook on the Correct Use of AI), which provided a consistent and reproducible framework for scoring participant prompts.

Identifying the criteria for a high-quality benchmark prompt was a multi-step process. In the initial phase of the research design, several large-scale datasets were examined to identify whether a standardized "optimal prompt" for planning tasks with GenAI already existed. These included BIG-bench (Beyond the Imitation Game Benchmark), ACPBench, and PlanBench. BIG-bench is a collaborative benchmark developed to test large language models (LLMs) across over 200 tasks involving reasoning, commonsense, and planning. ACPBench focuses on symbolic planning and action logic, while PlanBench, hosted on Hugging Face, targets plan generation and verification for language agents in structured environments. While initially promising, these datasets proved unsuitable for the study's core focus. Their primary function is to evaluate the internal reasoning and task performance of LLMs, not to support human users in learning to prompt more effectively or develop AI literacy. In other words, they benchmark models, not humans.

However, further exploration of BIG-bench led to the discovery of the STRATEGYQA task, and the accompanying paper *Did Aristotle Use a Laptop?* (Geva et al., 2021). This work offers insight into how large language models (LLMs) internally process prompts that require multi-step reasoning, even when those steps are not made explicit in the user's input. This represents what this thesis terms the "back-end" perspective - understanding the kind of structure and logic that help GenAI generate more accurate, contextually appropriate responses. According to Geva et al. (2021, pp. 346-347), if a prompt requires multi-step reasoning that is not explicitly stated - and the model is either unable to reconstruct this hidden logic on its own, or the user fails to guide it effectively - then the output will likely be flawed, even if the model holds the necessary factual knowledge. This principle reflects the core premise of the STRATEGYQA benchmark: the model is expected to reconstruct missing reasoning steps on its own, a process referred to as implicit decomposition.

For the purposes of this thesis, a high-quality prompt is defined as one that minimizes the assumptions the model must infer, while simultaneously encouraging multi-step reasoning. In essence, effective prompts are accurate, coherent, and context-rich, enabling the model to construct an appropriate internal reasoning pathway. To complement this back-end perspective, the thesis also draws on Ekin's (2023) practical framework for prompt engineering - a front-end approach that focuses on how users can deliberately shape prompts for better outputs. According to Ekin (2023, p. 4), effective prompts are clear, specific, context-informed, constraint-rich, and iteratively refined. Ambiguity, in contrast, significantly reduces prompt quality. Both the front-end and back-end perspectives converge on the insight that high-quality prompts are those that reduce ambiguity (i.e., they leave nothing for the model to assume) and provide the model with sufficient contextual information to accurately guide its multi-step reasoning process.

Cognitive Dimensions of Prompt Quality: Anticipation and Metacognition. This thesis treats metacognition and anticipation as essential cognitive dimensions of AI literacy, each playing a critical role in effective prompt construction. While both constructs are captured in the self-reported AI literacy scale, they are not evaluated as separate variables in the performance-based task. Instead, this study considers them to be indirectly reflected in participants' prompt quality. Metacognition and anticipation function as underlying cognitive processes that inform the criteria used in the prompt evaluation rubric (see Table 3). This rubric is adapted from Ekin's (2023) work, which implicitly incorporates metacognitive and anticipatory reasoning across its dimensions.

To elaborate, metacognition refers to a user's ability to reflect on their own thinking during prompt design - considering factors such as clarity, specificity, and their goal. This reflective process directly influences the model's capacity to produce relevant and coherent outputs. For instance, asking ChatGPT to "summarize photosynthesis in three lines" rather than just "explain photosynthesis" reflects metacognitive awareness of output goals and controls output verbosity (Ekin, 2023, p.5). It would be difficult to score highly on goal precision without engaging in such metacognitive reflection.

Functioning as a distinct but complementary process, anticipation involves the ability to foresee potential misunderstandings, errors or limitations in the AI's response and proactively include contextual information or constraints to mitigate them. A user who specifies a budget or time frame - e.g., "Plan a 3-day trip to Rome under €300" - is engaging in anticipatory reasoning, guiding the model to stay within practical boundaries via the use of constraints. Without anticipation, high scores on constraint or ambiguity control would be unlikely. Thus, although not directly measured, anticipation is inferred as a cognitive basis for literate prompt use. In fact, this thesis links anticipation directly to *use*, highlighting how critical foresight transforms basic engagement into literate interactions (see Figure 4 above).

Defining a High-Quality Prompt. Based on the dimensions outlined above, this study defines a high-quality prompt as one that enables the model to infer an appropriate reasoning pathway with minimal ambiguity. Such prompts are expected to include the following elements:

- Being precise about goals (e.g., "Plan a 3-day trip to Paris... I want to see the Eiffel Tower")

- Providing constraints and domain specificity (e.g., "...with a €500 budget and vegan food preferences")
- Controlling verbosity, by specifying the desired level of detail or output format (e.g., "Create a bullet-point agenda for each day"), and
- Demonstrating model understanding, such as by asking, "Is there any other information you need/ Is anything unclear?" - a technique that anticipates ambiguity and encourages clarification.

Accordingly, the benchmark prompt developed for this study's performance task is as follows:

> *"Plan a 3-day trip to Paris for a solo traveller with a budget of €500. The traveller is vegan, enjoys museums and scenic walks, and wants to see the Eiffel Tower. Please organize the itinerary by day, include estimated costs, and format the response as a bullet-point agenda. Let me know if you need any additional information to complete the plan."*

This operational definition informed both the construction of the benchmark prompt and the development of the scoring criteria used in the quasi-experiment.

Table 3.

Codebook on the Correct Use of AI (Prompt Score) - Content Analysis.

Dimension	Score 0	Score 1	Score 2	Note
Goal Precision	Generic task with no location or time frame (e.g., *"Plan a trip"*)	Adds one specific element (e.g., *"Plan a trip to Paris"*)	Fully defined objective, including duration and task structure (e.g., *"Plan a 3-day trip to Paris with an itinerary"*)	
Constraints / Specificity	No constraints provided (e.g., no info on budget, preferences, or travel type)	Includes one general or vague constraint (e.g., *"Not too expensive," "I'm vegetarian"*)	Clear and specific constraints given (e.g., *"A vegan traveller, budget of €500, wants to see the Eiffel Tower"*)	
Verbosity Control	No guidance on output length or structure (e.g., *"Plan my trip"*)	General phrasing, possibly vague (e.g., *"Give some ideas," "Keep it short"*)	Explicit formatting requested (e.g., *"Organize by day," "Use bullet points," "Organize by morning, afternoon, evening"*)	
Model Understanding / Ambiguity Mitigation	No awareness of the model's behaviour or limitations; prompt assumes human inference or mind-guessing abilities (e.g., *"Plan a trip," "Tell me what to do," "Make it cool"*) ----- **Coding tip:** If the prompt was given	Basic or general instructions, but still leaves ambiguity. User doesn't anticipate how ambiguity will affect output quality (e.g., *"Include meals and sights if possible", "add anything else you think is good"*)	Proactive awareness of AI limitations; includes clarifying language or checks (e.g., *"Let me know if you need more info," "Format as bullet points and include costs," "Avoid suggesting meat-based meals, the traveller is vegan" "Make sure*	**Coding tip:** Greetings, politeness, and signoffs (e.g., "Hi," "please," "thanks") should be ignored for this category unless they are used in place of functional instructions or signal a misunderstanding

	to a stranger and they would need to directly ask a question such as: *where? when? how? what?* the prompt received a 0.		*traveller sees Eifel Tower")*	of how generative AI works.
Domain Context	Overly general with no meaningful situational detail (e.g., *"Plan a vacation"*)	Some relevant terms or limited context (e.g., *"I want to go to Paris," "I'm a student," "I have a limited budget"*)	Richly contextualized with user traits, add specific likes and/ or dislikes and goals (e.g., *"Solo traveller who's vegan, enjoys museums and scenic walks, and wants to see the Eiffel Tower, looking for a relaxing 3-day itinerary in Paris with a €500 budget"*)	

Note. Source: Own interpretation. For more details visit Appendix B: Codebook Manual.

Constructing The Correct_Use Variable from Prompt Evaluation Scores. Each participant's prompt was scored using the evaluation rubric presented in Table 3: Codebook. The final variable, Correct_Use, represents the sum of five scored dimensions, with a maximum score of 10. For analysis purposes, all five dimensions - goal precision, constraint specificity, verbosity control, model understanding**,** and domain context - were equally weighted, with each receiving a maximum of 2 points.

The scoring process began with manual evaluation of all pre-test participants prompts by the researcher to establish initial benchmarks, identify recurring patterns, and reduce interpretive ambiguity. These pre-test scores contributed to the development of the codebook itself. Once the rubric was finalized, these prompts were re-used to test whether ChatGPT could be “trained” to apply the evaluation criteria. Given that ChatGPT had assisted throughout the thesis - including during the experimental design phase - it was already familiar with both the rubric and the broader context. Nonetheless, it was deliberately re-prompted with the necessary information to ensure consistency.

To facilitate automated scoring, the dataset was exported from SPSS and stripped of all variables except participants’ emails (used for later feedback) and their prompts. The first attempt involved prompting ChatGPT to apply the rubric directly to the raw text, which was uploaded via an Excel file. However, this yielded unreliable scores. In response, an iterative refinement process was launched to co-develop a more detailed, LLM-friendly “codebook manual” (see Appendix B). This involved repeatedly asking ChatGPT what kinds of instructions or clarifications it required to apply the codebook more accurately - i.e., in a more “human-like” manner.

Once a robust version of the manual was complete, another batch-scoring attempt was made. While ChatGPT showed improved consistency on small, supervised subsets of data (e.g., five prompts at a time with real-time feedback), it again failed to maintain accuracy and reliability when applied to the full dataset. At this point, the approach shifted to a hybrid method: each prompt was assessed one-by-one, with ChatGPT offering a proposed score and rationale, and the researcher determining whether to accept or override the decision. This method proved effective, as ChatGPT was generally accurate when asked to “think aloud” about individual prompts; however, its ability to generalize across multiple examples remained limited. Notably, even prompts that had been “trained on” and correctly scored during the think-aloud phase were misclassified when reintroduced in the full dataset.

A key limitation in ChatGPT’s scoring performance was its inability to consistently recognize semantically equivalent phrases unless they precisely matched the keywords used in the codebook. For instance, a prompt such as *“Plan a trip to Paris”* received a score of 1/2 for goal precision (as “Paris” was featured in the example), whereas the structurally identical *“Plan a trip to Milan”* was misclassified with a score of 0/2. This rigidity in keyword matching proved to be a persistent obstacle that could not be fully resolved; even with several rounds of back-and-forth adjustments followed, guided by concrete examples and corrective feedback.

Ultimately, all 74 valid prompts were scored manually. Prompts that were incomplete, off-topic, or mistakenly submitted as AI-generated output rather than human-written instructions were assigned a placeholder score of 15 and excluded from analysis. Valid prompt scores ranged from 0 to 10. Descriptive statistics revealed substantial variation in participants' ability to construct high-quality prompts ($M = 3.43$, $SD = 2.25$), with the most frequent score being 1 (25.7%), suggesting that most participants produced only minimal functional instructions and often lacked the clarity or specificity required for literate AI use.

Construction of Self-Reported Variables

While *correct use* captures participants' demonstrated ability to communicate effectively with generative AI, the present section addresses their *perceived competence***.** This self-reported dimension of AI literacy provides insight into participants' attitudes, beliefs, and psychological dispositions, including perceived usefulness, and trust towards generative AI. In addition to the AILS, this section outlines the use of validated scales such as the TAM subscales, adapted instruments such as the NARS and custom-developed items such as those related to metacognition and anticipation that were used in the survey portion of this study.

To ensure construct validity, a scale validation strategy was implemented based on item origin. For adapted multi-item scales with minor rewording (e.g., Perceived Usefulness, Functionality Trust), internal consistency was assessed via Cronbach's alpha. Custom-developed scales, such as *Feels Like Cheating*, were evaluated through both Cronbach's alpha and exploratory factor analysis (EFA). The four custom items representing metacognition and anticipation were included in an EFA together with the original AILS items. These items loaded together on a distinct factor, validating them as a unified higher-order component of AI literacy (AMAILS). Single-item indicators (e.g., Uncanny Valley discomfort) were reported descriptively, in line with standard practice.

AI Literacy. As discussed, this thesis conceptualizes AI literacy as a multidimensional construct encompassing not only technical competence but also reflective, evaluative, and anticipatory abilities in interactions with GenAI. Drawing from the foundational theory of Long and Magerko (2020) and Yi (2021), AI literacy is operationalized using a composite measure that blends established self-reported scales with new items tailored to this study's specific hypotheses and context.

The primary scale used in this study is the Artificial Intelligence Literacy Scale (AILS) developed by Wang, Rau, and Yuan (2023). This 12-item, self-reported instrument was specifically designed to measure ordinary users' competence in interacting with AI systems across four validated subscales: Awareness, Usage, Evaluation, and Ethics. The AILS includes questions like "I do not know how AI technology can help me" (scale item 2, a reverse-coded item) and "I can skilfully use AI applications or products to help me with my daily work" (scale item 4). It uses a 7-point Likert scale, a format selected by the original authors for its suitability in electronically distributed surveys and its ability to capture nuanced participant responses (Wang et al., 2023, p. 1329).

In the context of this thesis, the *Awareness* and *Evaluation* components of the AILS are interpreted as indicators of data literacy and metacognition, respectively. *Usage* aligns with the construct of anticipation and *Ethics* captures the user's ability to interact with GenAI in a socially responsible and context-aware manner. There is a link between ethics and model understanding as well - further contributing to one's overall level of AI literacy. The AILS provides a robust foundation for measuring each participant's self-reported level of AI literacy, enabling comparisons across both correct use and acceptance of GenAI in subsequent analyses. The full list of AILS items used in this study can be found in Appendix C: Original Artificial Intelligence Literacy Scale (AILS).

To ensure the cognitive dimensions of metacognition and anticipation were fully captured and given appropriate weight in the analysis, four custom-developed items were introduced - two targeting metacognition and two targeting anticipation. These additions expand the conceptual framework of AI literacy by integrating higher-order thinking skills that are particularly prevalent among AI-literate users and relevant to navigating complex interactions with GenAI (Long & Magerko, 2020; Yi, 2021).

The metacognition subscale was designed to assess participants' awareness and regulation of their own cognitive processes while engaging with GAI. This construct aligns with Hypotheses H1b and H2, which explore how self-reflective thinking supports effective prompt formulation, leading to correct use of GenAI and, ultimately, workplace acceptance. The two custom-made items include: *"I reflect on how I formulate prompts when using AI tools"* and *"I think about what made an AI response effective or ineffective."* Responses were measured on a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5).

The Anticipation subscale measures participants' ability to foresee possible limitations or misunderstandings by GenAI before submitting a prompt. This construct supports Hypotheses H1a and H2. The two custom-made items include: *"Before using AI, I consider what kind of instructions will likely generate a good response"* and *"I try to think ahead about what might be misunderstood by generative AI when I write my prompt."* These items were also measured on a 5-point Likert scale.

The Construction and Validation of an Expanded AI Literacy Scale. The AI Literacy Scale (AILS; Wang et al., 2023) was used to assess self-reported AI literacy across four subdimensions: Awareness, Usage, Evaluation, and Ethics. A Priori Criteria were examined, and two negatively worded items were reverse coded in accordance with the original authors' guidelines:

- "I do not know how AI technology can help me" (*AW2_rev_Idonot_AILS*)

- "I am never alert to privacy and information security issues" (*E11_rev_Iamnever_AILS*)

An initial reliability analysis of the original 12 *AILS* items yielded a Cronbach's alpha of $\alpha = .68$, indicating questionable internal consistency. One item - "It is usually hard for me to learn to use a new AI application or product" - showed a negative item-total correlation ($r = -.59$) and was subsequently reverse-coded to align directionality (*U5_rev_itisusually_AILS*).

To expand the scale's conceptual coverage, the four custom items targeting metacognition and anticipation - core components of AI literacy (Yi, 2021) - were subsequently added. After applying all reverse-coding and integrating the additional items, a second reliability analysis showed improved internal consistency ($\alpha = .80$), indicating acceptable reliability, and supporting the validity of the expanded scale.

A Principal Component Analysis (PCA) with direct oblimin rotation was conducted to explore the dimensional structure of the revised AILS scale. Assumptions for factor analysis were met: the Kaiser-Meyer-Olkin (KMO) measure was .793, indicating adequate sampling adequacy (Kaiser, 1970), and Bartlett's Test of Sphericity was significant, $\chi^2(120) = 478.12$, $p < .001$, confirming sufficient inter-item correlations (Bartlett, 1954). While the number of valid cases ($N = 86$) falls below the commonly recommended threshold of 150 for factor analysis, the analysis still offers informative exploratory insights into the scale's underlying structure. The five extracted components together explained **67.16%** of the total variance in the revised AILS items. Specifically, Component 1 accounted for **30.29%**, Component 2 for **12.66%**, Component 3 for **10.17%**, Component 4 for **7.68%**, and Component 5 for **6.35%** of the variance.

Based on eigenvalues greater than 1, five components were extracted. Inspection of the pattern matrix revealed that all four custom metacognition and anticipation items-"I reflect on how I formulate prompts," "I think about what made a response effective or ineffective," "I try to think ahead about what might be misunderstood," and "I consider what kind of instructions will likely generate a good response"-loaded strongly on a single factor (Component 2), with loadings ranging from –.80 to –.845. This supports their conceptual coherence as a shared dimension within AI literacy. A full summary of factor loadings and reliability statistics is presented in Table 4.

This result indicates that, empirically, the metacognition and anticipation items reflect a shared underlying construct and do not separate cleanly into distinct subdimensions. Accordingly, they were treated as a unified higher-order competency within the broader AI literacy construct. As a result, the original sub-hypotheses *H1a* (metacognition) and *H1b* (anticipation) were not pursued independently. However, *H1*, stating that higher levels of AI literacy are positively associated with acceptance of GenAI in workplace-like contexts, was retained. This supports the theoretical claim that anticipatory and reflective prompting skills represent a cohesive, higher-order component of AI literacy (Yi, 2021).

To streamline subsequent analyses, a composite variable - the Expanded Artificial Intelligence Literacy Scale (AMAILS) - was computed by averaging 16 items: 12 from the original AILS (Wang et al., 2023) and 4 custom-developed items capturing metacognition and anticipation (Yi, 2021). All reverse-coded items were adjusted prior to computation. The resulting scale demonstrated acceptable internal consistency, $\alpha = .80$, supporting its use as a unified measure of AI literacy. Note that subscale-level alphas are not reported, as the scale is treated as a unified construct in this study. Descriptive statistics showed a moderate level of AI literacy, $M = 3.59$, $SD = 0.41$, range = 2.56–4.56 (5-point scale). Although AILS used a 7-

point scale and the custom items a 5-point scale, no rescaling was performed to preserve interpretability.

Table 4.

Pattern Matrix Showing Factor Loadings for Items in the Expanded AI Literacy Scale (AMAILS)

	Component				
Item	**1**	**2**	**3**	**4**	**5**
I can choose the most appropriate AI application or product from a variety for a particular task.	.78				
I can skilfully use AI applications or products to help me with my daily work.	.77				
I can identify the AI technology employed in the applications and products I use.	.72				.43
I can distinguish between smart devices and non-smart devices.	.60			.33	
I can choose a proper solution from various solutions provided by a smart agent.	.57				
I think about what made a response (from the generative AI tool) effective or ineffective.		-.84			

Before using generative AI, I consider what kind of instructions will likely generate a good response.		-.84			
I try to think ahead about what might be misunderstood by generative AI when I write my prompt.		-.82			
I reflect on how I formulate prompts when using generative AI tools.		-.80			
I can use AI applications or products to improve my work efficiency.		-.43			-.39
I always comply with ethical principles when using AI applications or products.			.84		
I do not know how AI technology can help me. *(reversed)*			-.63	.40	
I am never alert to privacy and information security issues. *(reversed)*				.82	
I can evaluate the capabilities and limitations of an AI application or product after using it for a while.	.30			.59	
It is usually hard for me to learn to use a new AI application or product. *(reversed)*	.37			.52	
I am always alert to the abuse of AI technology.					.89
R^2	.30	.13	.10	.08	.06

See Appendix D (*SPSS* Screenshots 3, 4, 5) for Total-Item Statistics, the pattern matrix, and the *AMAILS* computation, respectively.

Xenophobia Toward GenAI. To measure socio-emotional discomfort and aversion toward GenAI, this study adapts the Negative Attitudes Toward Robots Scale (NARS) by Nomura et al. (2006). Following Hong's (2021, p. 1026) precedent, each item is adapted by replacing "robots" with "generative AI" to suit the context of non-embodied AI tools such as ChatGPT. NARS is particularly relevant to this thesis as it reflects key dimensions of xenophobic resistance: workplace discomfort, distrust of emotionally expressive AI, and concerns about AI's societal dominance. These domains align with behavioural, emotional, and ideological rejection of GenAI, supporting the conceptual basis for Hypothesis 3, which posits xenophobia as a mediator between AI literacy and GenAI acceptance.

Rather than using the full 14-item NARS instrument, this study selects five items that best align with this thesis. Drawing primarily from the original subscales of interaction discomfort (S1) and social influence concern (S2), these items capture different dimensions of socio-emotional resistance, including discomfort using GenAI at work, fear of social judgment, and concerns about overreliance. Items related to emotional unease (S3) are excluded, as they focus on affective bonding with robots; an area outside the scope of this study. All adapted items were measured using the original 5-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), as used in the original NARS. The full adaptation is in Table 5 below.

Table 5.

Adaptation of NARS Items for GenAI *Context*

Original Item	Subscale	Adapted GenAI Version	Relevance to Thesis Constructs
"I would feel uneasy if I was given a job where I had to use robots."	S1: Interaction Discomfort	"I would feel uneasy if I was given a job where I had to use generative AI."	Captures general workplace-specific unease. Central to behavioural resistance to GenAI adoption in professional tasks.
"I would feel nervous operating a robot in front of other people."	S1: Interaction Discomfort	"I feel nervous using generative AI in front of other people."	Reflects social discomfort/taboo and fear of judgment - highly relevant to workplace and might be related to "feels like cheating" perspective.
"I would hate the idea that robots or artificial intelligences were making judgments about things."	S2: Social Influence Concern	"I would hate the idea that generative AI is making judgments about things that affect me."	Captures concern over decision-making power and perceived encroachment on human authority.
"I feel that if I depend on robots too much, something bad might happen."	S2: Social Influence Concern	"I feel that if I depend on generative AI too much, something bad might happen."	Reflects overreliance anxiety and loss of control - key to emotional resistance and trust concerns.
"I feel that in the future society will be dominated by robots."	S2: Social Influence Concern	"I feel that in the future society will be dominated by generative AI."	Measures existential fear and macro-level rejection of GAI. Central to ideological resistance and H3.

Note. Source: Own interpretation.

A reliability analysis was conducted on five items adapted from the Negative Attitudes toward Robots Scale (NARS; Nomura et al., 2006) to measure xenophobia toward GAI. Internal consistency was questionable, $\alpha = .68$. Inspection of item-total correlations revealed that the item *"I feel that in the future society will be dominated by generative AI"* had a weak corrected item-total correlation ($r = .16$), and its removal increased Cronbach's alpha to $\alpha = .73$. This item was excluded from further analysis.

A composite variable (*xenophobia_GAI*) was computed using the remaining four items. The scale demonstrated acceptable internal consistency, $\alpha = .73$. Descriptive statistics showed a moderate level of xenophobia toward GenAI, $M = 2.66$, $SD = 0.95$, range = 1.00-5.00.

The Uncanny Valley of Outputs. Wu (2023) emphasizes that AI's human-like outputs (in their work: art) can evoke the Uncanny Valley effect; even in the absence of a physical robot. Rather than proposing a reusable scale, Wu (2023) developed custom items grounded in experimental design. Importantly, their study concluded with a call for future research to examine the "social uncanny valley" across diverse contexts and AI-generated content to better understand the psychological and social dynamics behind user discomfort and resistance.

This thesis responds to that call by extending the investigation into the workplace context and text-based outputs of GAI. While the adaptation of the NARS scale provides a foundation for examination, one additional item - an original interpretation inspired by Wu (2023) - is included to capture users' discomfort when GenAI becomes too human-like in behaviour or output:

"Generative AI that acts too humanlike makes me uncomfortable."

While this is a single-item measure (measured on 5- point Likert), it is theoretically grounded in Wu's (2023) findings and serves as a supplemental variable rather than a formal subscale. It captures a specific form of aesthetic and emotional discomfort, therefore reinforcing the theoretical foundation for Hypothesis 3. Findings indicate that 27.3% of respondents agreed - at least to some extent - with the statement *"Generative AI that acts too humanlike makes me uncomfortable"*.

Together, the three NARS-based dimensions and this uncanny discomfort item allow for a more nuanced investigation of xenophobia as a mediator between AI literacy and acceptance. The full set of original NARS items and the adapted item from Wu (2023) can be found in Appendix E.

Trust and Workplace Acceptance. Acceptance of GenAI in the workplace is measured using a tailored version of the TAM, synthesized by Choung, and colleagues (2023). As briefly touched upon in a previous section, their model responds to recent scholarly critiques of TAM's limitations when applied to agent-like technologies such as (generative) AI (Koenig, 2024). Specifically, they expand the classic TAM framework by integrating trust as a multidimensional construct, adding functionality trust and human-like trust. Their findings confirm that trust indirectly impacts GenAI usage intentions through perceived usefulness and user attitudes - a pathway well-aligned with Hypothesis 4 (Choung et al., 2023, p. 1734).

This thesis incorporates selected items from Study 2 of Choung et al. (2023), adapted to focus on "generative AI" tools rather than "smart technologies" as originally phrased. All items were rated on a 5-point Likert scale. Specifically, the included constructs are:

- Functionality Trust, assessing perceptions of GAI's competence and reliability (e.g., *"Generative AI tools work well"*);

- Perceived Usefulness, capturing the extent to which GenAI enhances productivity (e.g., *"Using generative AI tools would enable me to accomplish tasks more quickly"*); and

- Attitude Toward GenAI, reflecting general affective evaluations (e.g., *"Using generative AI tools is a good idea"*).

Together, these constructs provide the empirical foundation to test both H1 and H4, while contributing to ongoing efforts to update technology acceptance frameworks for AI-specific contexts. Specifically, perceived usefulness and attitude were combined to represent acceptance of GenAI, while functionality trust was modelled separately as a potential mediator (H4).

To ensure conceptual clarity and reduce survey redundancy, several TAM subdimensions are deliberately excluded. Perceived ease of use is omitted due to its conceptual overlap with AI literacy, which already captures participants' confidence and usage competence. Behavioural intentions are excluded, as this study instead captures resistance and hesitation through xenophobia, using adapted items from the NARS and Uncanny Valley literature. Lastly, human-like trust is not included, since it does not fall within the scope of this thesis. The full set of original items is available in Appendix F, while the adapted version used in this thesis, including the complete questionnaire, is provided in Appendix G.

Reliability analyses were conducted to assess the internal consistency of each scale. The *Perceived Usefulness* scale (5 items) demonstrated excellent internal consistency, α = .89, with M = 21.46, SD = 3.48. The *Attitude Toward GenAI* scale (4 items) showed similarly high reliability, α = .90, with M = 16.14, SD = 3.45. The *Functionality Trust* scale (5 items) also showed strong internal consistency, α = .87, M = 17.82, SD = 4.07. All scales exceeded the recommended minimum reliability threshold of α = .70, supporting the computation of composite variables.

In line with this, a new composite variable, Acceptance_GAI_TAM, measuring acceptance of GenAI in workplace contexts was created by combining 9 items from Perceived Usefulness (5 items) and Attitude Toward GenAI (4 items). The combined scale showed excellent internal consistency, α = .92. Participants reported generally high acceptance, M = 4.17, SD = 0.72, range = 2.11-5.00 (5-point scale). Higher scores indicate stronger perceived usefulness and more positive attitudes toward GenAI tools. Additionally, a second composite variable, Trust_Function_TAM, was computed to assess functional trust in GenAI. This 5-item scale demonstrated strong reliability, α = .87. The variable indicated a moderate-to-high trust level: M = 3.56, SD = 0.81, range = 1.00-5.00.

The "Feels Like Cheating" Perception. This study introduces Hypothesis 5 where, in summary, *"Using ChatGPT to help with work feels like cheating"* arises as a psychological response to the disruption of traditional motivation and organizational psychology frameworks, particularly Vroom's Expectancy Theory and Deci and Ryan's Self-Determination Theory. No validated scale currently exists to assess this perception in the context of AI-assisted task execution. As such, this thesis developed a set of five original items to measure the construct of *cheating perception* in a professional or academic setting.

These items were designed to reflect expectancy, instrumentality, and valence, the three core components of Vroom's framework, capturing the cognitive and emotional disconnect that may arise when individuals delegate substantial portions of task execution to GenAI tools. Participants responded to each item using a 5-point Likert scale ranging from strongly disagree (1) to strongly agree (5). The five items are:

1. *Using generative AI tools makes me feel like the results aren't truly mine.*
2. *I feel guilty submitting work that was heavily assisted by generative AI.*
3. *Using generative AI reduces my sense of achievement.*
4. *Using AI to help with work feels like cheating.*
5. *I feel uncomfortable relying on AI to complete professional tasks.*

Together, these items aim to capture a latent construct of psychological discomfort and diminished ownership. Accordingly, a reliability analysis took place, the new, five-item scale demonstrated excellent internal consistency, $\alpha = .89$. As such, a composite variable, *Cheating_Feels*, was computed as the mean score of the five items. Descriptive statistics indicated moderate levels of perceived discomfort, $M = 3.13$, $SD = 1.07$, range = 1.00-5.00.

Table 6.

Summary of Measurement Tools in Relation to Hypotheses

Construct	Measurement Tool	Relevant Hypotheses
AI Literacy	Artificial Intelligence Literacy Scale (AILS - Wang et al., 2023) and metacognition and anticipation custom scales	H1, H2, H5
Metacognition	Custom subscale (2 items), self-developed	H1b, H2
Anticipation	Custom subscale (2 items), self-developed	H1a, H2
Correct Use of GAI	Performance-based task scored via The Codebook on the Correct Use (Table 3)	H2
Trust	Functionality Trust (Study 2, Choung et al., 2023)	H4
Workplace Acceptance	TAM-based items: Perceived Usefulness + Attitude Toward GenAI (Choung et al., 2023)	H1, H3, H4
Feels Like Cheating	Custom 5-item scale based on Expectancy Theory and Self-Determination Theory	H5
Xenophobia	Adapted from Nomura et al.’s NARS Scale and Uncanny Valley literature	H3

Participant Journey Through the Study

The quasi-experiment used to test this thesis’s hypotheses was administered via an online survey. Participants first provided informed consent, as per standard procedures. They then proceeded to a brief introductory section that defined “Generative AI” and “prompt” to ensure a shared understanding. Participants were then asked two preliminary questions regarding their prior experience with GenAI tools and whether the use of such tools was permitted in their academic or professional environments. This was followed by a short demographic questionnaire.

Next, participants were asked to complete the experimental task (see Appendix H for full instructions provided to participants). Upon completing the task, they responded to a series of self-report measures in the following order: AILS (Wang et al., 2023); perceived usefulness, attitude toward generative AI, and functionality trust (adapted from Choung et al., 2023); the four custom-developed items capturing metacognition and anticipation; the item inspired by the Uncanny Valley; the xenophobia toward GenAI scale (adapted from Nomura et al., 2006 and informed by Hong, 2021); and the questions related to the perception that using GenAI “feels like cheating”. Finally, participants were invited to provide their email address if they wished to receive personalized feedback on their AI literacy prompt score.

Pre-Test and Pilot Phase

Before full data collection, a pre-test was conducted with 10 participants, including friends, family members, and colleagues - many of whom hold advanced degrees or are researchers themselves. This highly educated sample was deliberately chosen to elicit detailed and constructive feedback that would enhance the clarity, validity, and reliability of the study design. Participants completed the full survey and experimental task, after which they provided open-ended comments on usability, flow, and question phrasing.

Three key revisions followed. First, one participant flagged confusion with the custom anticipation item: “I try to anticipate what information the AI might misunderstand or ignore.” This was reworded for clarity to: “I try to think ahead about what might be misunderstood by generative AI when I write my prompt”. Second, feedback revealed uncertainty around the quasi-experiment instructions - specifically whether participants should submit their own prompt or ChatGPT’s response. To clarify, the task instructions were revised to read: “Only share the instructions YOU gave to ChatGPT”. Third, a participant commented on institutional restrictions surrounding AI use. In response, a new item was added to capture this context: “Are you allowed to use generative AI (like ChatGPT) at work or school?” using a 5-point Likert scale with policy-oriented response options.

Overall, the pilot phase ensured that the final instrument was more intuitive, precise, and well-aligned with the goals of the quasi-experimental design. In line with standard research ethics and to avoid bias in the main analysis, the data collected during the pre-test phase was excluded from the final dataset.

Ethical Consideration

This research complies with the Code of Conduct for Research Integrity as established by the Netherlands Association of Universities (VSNU). All procedures involving human participants were designed with ethical transparency and data protection in mind. Participants were informed about the general purpose of the study and their rights as participants, including the option to withdraw at any time without penalty.

Participants were assured of anonymity and confidentiality in data handling, and explicit informed consent was obtained before participation. The use of collected data was communicated clearly, and all data were stored and processed in accordance with university data management protocols.

For a full overview of ethical compliance and safeguards, including consent procedures and debriefing materials, see Appendix I: Ethics Checklist.

Results

This section presents the results of the hypothesis tests, beginning with simple linear regressions that examine the direct relationships between self-reported AI literacy and key outcome variables: acceptance of generative AI (H1), correct use of generative AI (H2), and perceptions of “cheating” (H5). To further explore whether actual performance (rather than self-perception) offers better predictive power, follow-up analyses were conducted using participants’ prompt scores as an alternative predictor. Finally, a mediation model (PROCESS Macro Model 4) tested whether emotional variables-trust and xenophobia-mediate the relationship between AI literacy and GenAI acceptance (H3 and H4). While all statistically relevant information is reported below, supplementary SPSS output screenshots are available in Appendix D.

Accordingly, Hypothesis 1 proposed that higher levels of self-reported AI literacy are positively associated with the acceptance of generative AI technologies in the workplace. To test this A simple linear regression was conducted with acceptance of generative AI as the dependent variable and self-reported AI literacy as the predictor. The model was not statistically significant, $F(1, 71) = 0.410$, $p = .524$, $R^2 = .006$. AI literacy did not significantly predict GenAI acceptance, $\beta = –.08$, $p = .524$. Thus, Hypothesis 1 was rejected. No evidence was found to support the proposed positive association between self-reported AI literacy and GenAI acceptance in this sample.

Next, Hypothesis 2 proposed that higher levels of self-reported AI literacy are positively associated with the correct use of generative AI technologies. To test this, a simple linear regression was conducted with prompt quality as the dependent variable and self-reported AI literacy as the predictor. The model was not statistically significant, $F(1, 72) = 0.005$, $p = .943$, $R^2 = .000$. AI literacy did not significantly predict prompt quality, $\beta = –.01$, $p = .943$. Therefore, Hypothesis 2 was rejected. No evidence was found to support the proposed positive association between self-reported AI literacy and correct use of generative AI.

Further, Hypothesis 5 proposed that higher levels of self-reported AI literacy are negatively associated with the belief that using generative AI tools feels like cheating. To test this, a simple linear regression was conducted with perceived cheating as the dependent variable and self-reported AI literacy as the predictor. The model was not statistically significant, $F(1, 72) = 2.34$, $p = .130$, $R^2 = .031$. AI literacy did not significantly predict perceptions of cheating, $\beta = .18$, $p = .130$. Thus, Hypothesis 5 was rejected. Although the direction of the coefficient suggests that those with higher AI literacy may be slightly more likely to view GenAI use as cheating (contrary to expectations), this association was not significant. As such, the perception of "cheating" when using generative AI does not appear to be meaningfully shaped by AI literacy levels in this sample.

Out of exploratory interest, a follow-up analysis examined whether participants' actual prompt performance-rather than self-reported AI literacy-would better predict acceptance of generative AI and perceptions of "cheating" (adaptations of Hypotheses 1 and 5). As a first step, a Pearson correlation tested whether self-reported AI literacy was associated with prompt quality. No significant relationship was found, $r(74) = –.01$, $p = .943$, suggesting a disconnect between perceived and demonstrated competence.

Building on this, a simple linear regression was conducted to test whether prompt quality predicted acceptance of generative AI. The model was not statistically significant, $F(1, 71) = 0.11$, $p = .740$, $R^2 = .002$. Prompt quality did not significantly predict GenAI acceptance, $\beta = .04$, $p = .740$. A second regression examined whether prompt quality predicted the belief that using GenAI tools feels like cheating. This model was also not statistically significant, $F(1, 72) = 0.14$, $p = .711$, $R^2 = .002$. No meaningful relationship was found between prompt performance and perceptions of cheating, $\beta = .04$, $p = .711$. In short, using actual performance instead of self-reported literacy as a predictor did not meaningfully change the findings.

To test whether trust and xenophobia mediate the relationship between AI literacy and the acceptance of GenAI, a parallel mediation analysis was conducted using PROCESS Macro Model 4 (Hayes, 2022), with 5,000 bootstrap samples and a 95% confidence interval. In compliance with PROCESS syntax requirements, variable names were shortened: AMAILS (X), Trst_TAM (M), Xeno_GenAI (M), and acpt_GenAI (Y).

The overall model predicting acceptance of GenAI was significant, $R^2 = .60$, $F(3, 83) = 42.08$, $p < .001$, indicating that AI literacy and the two mediators together explained 60.3% of the variance in GenAI acceptance. However, the direct effect of AI literacy on acceptance was not significant, $B = 0.18$, $SE = 0.12$, $t = 1.50$, $p = .137$, 95% CI [-0.06, 0.42].

Regarding the indirect effects, neither mediation pathway reached statistical significance. The indirect effect of AI literacy on acceptance through trust was $B = -0.11$, bootstrap 95% CI [-0.35, 0.14], and through xenophobia was $B = -0.08$, bootstrap 95% CI [-0.23, 0.03]. The total indirect effect was also non-significant, $B = -0.19$, bootstrap 95% CI [-0.51, 0.12].

However, despite the lack of significant mediation, both mediators were individually significant predictors of acceptance. Trust was positively associated with acceptance, $B = 0.51$, $SE = 0.07$, $t = 7.42$, $p < .001$, 95% CI [0.38, 0.65], indicating that individuals who trust GenAI are more likely to accept it. Conversely, xenophobia was negatively associated with acceptance, $B = -0.23$, $SE = 0.06$, $t = -3.99$, $p < .001$, 95% CI [-0.35, -0.12], suggesting that greater fear or discomfort toward AI significantly predicts lower acceptance.

Nevertheless, Hypotheses 3 and 4 were rejected, as the mediating effects of xenophobia and trust, respectively, were not supported by the data. However, the significant paths from trust and xenophobia to acceptance highlight the critical role of emotional and psychological responses in shaping user attitudes toward GenAI - independent of AI literacy levels.

Discussion: Interpreting the Unexpected

Diverging from the initial expectations of this thesis, none of the tested hypotheses were supported by statistically significant results. However, several non-significant trends - particularly those involving trust, xenophobia, and the disconnect between self-reported AI literacy and correct use of GenAI - may still offer meaningful exploratory insights. For example, AI literacy was negatively associated with trust in GenAI and positively associated with xenophobia. While neither relationship reached statistical significance, both trends run counter to the hypothesized mediation: that increased AI literacy would enhance trust and reduce xenophobic attitudes toward GenAI. These unexpected findings do not support reliable claims but invite reflection and closer examination of the conceptual dynamics at play.

Conditional Trust

First this discussion delves into the unexpected trust results. A conservative interpretation is that increased AI familiarity naturally fosters greater caution. Participants with higher self-reported AI literacy may be more attuned to the risks, limitations, or ethical challenges of GenAI - such as hallucinated outputs or biased reasoning - and are therefore more critical of its use. This first interpretation suggests that lower trust in GenAI may in fact reflect a higher degree of discernment. This reasoning contrasts to the findings of Fernandes and colleagues (2024), who observed that technically proficient users often over-trusted AI outputs during task performance. In their study, trust appeared automatic and uncritical; in the present thesis results, trust may instead be conditional.

The observed discrepancy - and ultimately the rejection of the mediation between AI literacy, trust, and acceptance – might be related to the concept of *"trust"* being too broadly or simplistically measured. While researchers have debated the efficacy of TAM in (generative) AI environments (Koenig, 2024), Choung and colleagues, (2023) usefully integrated functionality trust into the extended TAM. However, the trust items in this study might be too broad to capture the conditional mindset of AI-literate individuals.

Consider this, an AI-literate participant might respond to the statement *"Generative AI tools are reliable"* with a confident *"6/7 - yes, when I prompt it correctly".* That same person might also respond *"1/7 - no, if I don't prompt it properly, it hallucinates"*. Ironically, both responses would be accurate, depending on how the question is interpreted. Illustrating a key interpretive challenge: for users who understand prompt engineering and model limitations, trust is not binary. It is conditional, shaped by the context and quality of interaction. A generic Likert-scale item may therefore elicit discrepancies. Paradoxically, this could result in lower trust scores among more AI-literate participants, even though they engage more responsibly and effectively with the tool.

In this sense, the survey items may have unintentionally "flattened" trust by framing it as a fixed trait of the technology, rather than a dynamic judgment shaped by user behaviour. Future research should develop more nuanced trust instruments - incorporating concepts like conditional, calibrated, or relational trust (noted in future research section as well).

The Xenophobia Paradox

Second**,** the xenophobia findings also deviated from expectations. As outlined in Hypothesis 4, xenophobia was expected to mediate the relationship between AI literacy and acceptance of GenAI. However, mediation was not supported, AI literacy did not significantly predict xenophobia, and the indirect effect was non-significant. Nonetheless, xenophobia itself was a significant negative predictor of acceptance – this makes empirical sense; it underscores the emotional weight of discomfort and perceived threat, as discussed in the literature review section above (Hong, 2021; Wu, 2023; Davis, 1989). Interestingly, the observed (but non-significant) association between AI literacy and xenophobia was positive, running counter to the original hypothesis that increased literacy would reduce xenophobia. While no claims can be made about a reliable pattern in this sample, the unexpected directionality of this association invites reflection.

Why might individuals who consider themselves more AI-literate also report more discomfort, avoidance, or resistance (sentiments encapsulated by xenophobia)? One speculative explanation is that AI-literate users are more attuned to how GenAI challenges established boundaries between human and machine. Their knowledge may make them more aware of GenAI's growing capabilities, and thus more concerned about risks such as job displacement, ethical misuse, or social disruption. Rather than reacting out of an irrational fear to something "foreign", their discomfort may stem from precisely the understanding of (generative) AI's abilities – which are vast (Aydin & Karaarslan, 2023, p. 118). Under this syllogism, heightened AI literacy may not diminish xenophobia, but instead refine and intensify it (Hong, 2021; Wu, 2023).

This interpretation ("I understand what GenAI can do - thus, I am prejudiced toward it") prompts a reconsideration of how *technological xenophobia* was conceptualized in this thesis. While it was initially framed as a fear of the unknown - specifically referring to limited understanding of the technology - it may also encompass a fear towards *unknow futures*. For AI-literate individuals, discomfort may not stem from the technology itself, but rather from the uncertainty it introduces. Concerns about automation, job displacement, ethical instability, and the blurring of boundaries between human and machine are all plausible sources of unease. Additionally, the sample may include individuals actively navigating workplace shifts or fearing displacement - contexts in which greater awareness of AI's implications could intensify, rather than soothe, anxiety. In these cases, literacy might amplify recognition of structural threats rather than reduce discomfort.

Another possible explanation for the non-significant mediation of xenophobia lies in the Uncanny Valley effect. It is plausible that the xenophobia scale partially captured this phenomenon. To elaborate, 27.3% of participants agreed (to some extent) with the statement: "*Generative AI that acts too humanlike makes me uncomfortable*" (Appendix D: Screenshot 1), suggesting that roughly one-third experienced affective unease when confronted with human-like GenAI behavior. Notably, this item was not part of the xenophobia scale but was included separately to probe Uncanny Valley discomfort. As such, discomfort may arise independently, potentially reflecting an innate perceptual tension triggered when GenAI appears almost - but not entirely - human. In this sense, AI literacy and Uncanny Valley discomfort may co-exist; even those who fully grasp how GenAI works may still experience a deep phycological response when it crosses certain human-like thresholds. Accordingly, the absence of a mediating effect may reflect the affective depth of Uncanny Valley discomfort - one that operates below the level of conscious reasoning and is unaffected by AI literacy (Mori, 1970; Wu, 2023).

It is also plausible that AI literacy only reduces xenophobia under certain conditions- such as when accompanied by trust. Alternatively, it may be shaped by individual dispositional outlooks: whether individuals are optimistic or pessimistic in their worldview could influence how they interpret AI's trajectory. For example, even with high literacy, a pessimistic individual might perceive AI as a threat to agency or ethics, while an optimistic one may see opportunity and enhancement. While these are fascinating avenues for future inquiry (also denoted in the future research suggestions), they remain theoretical and unconfirmed in this study. What is empirically supported - and thus central to this discussion - is that xenophobia significantly and negatively predicts acceptance of generative AI. This reinforces the idea that negative feelings towards GenAI impact its use and adoption. When something is unfamiliar, unsettling, or difficult to situate within human–machine boundaries, emotional responses take over (Hong, 2021; Wu, 2023; Davis, 1989). In such cases, AI literacy offers a path to re-establishing psychological control (Yi, 2021).

AI Literacy: Perception vs. Performance

Although AI literacy is a mitigating factor for challenges such as mistrust, xenophobia, and misuse of generative AI, its operationalization remains contested. Given the unique, agent-like nature of GenAI, this thesis challenges the adequacy of (traditional) self-report instruments. As Koenig (2024) and Yi (2021) argue, frameworks like TAM and AILS may oversimplify the complex, context-sensitive demands that AI systems place on users. This critique is echoed in the present findings, where self-reported AI literacy (measured via AMAILS) showed no meaningful correlation with actual prompt task performance. Ideally, these two indicators would align, suggesting that perceived competence translates into applied skill. However, the data suggest otherwise.

The AMAILS scores averaged 3.59 (SD = 0.41) on an un-rescaled 6.5-point scale, indicating that participants generally considered themselves moderately literate. However, prompt scores ranged from 0 to 10, with a mean of 3.43 (SD = 2.25), and more than 25% of participants scored just one point. This contrast points to a significant gap between perceived and demonstrated competence. The lack of a statistically significant correlation between AMAILS and prompt quality further supports this conclusion (related to H2).

Several factors may explain this disconnect. One is the well-documented Dunning-Kruger effect, where individuals with lower skill levels tend to overestimate their abilities (Fernandes et al., 2024, p. 11). Another explanation is conceptual: self-reported literacy may reflect abstract familiarity (i.e. what participants *believe* they understand from for ex. media exposure) - rather than the concrete skills (such as anticipation, metacognition, digital literacy etc.) required for successful prompt design. Further, participants motivation is another consideration. While participants were told they would receive an AI literacy score, there is no guarantee that all approached the prompt task with focus or intention. A lack of engagement could have further distorted the performance results.

Ultimately, these findings suggest that measuring AI literacy requires more than asking users what they *think* they know. It demands evidence of what they can *actually* do. Self-reporting may still hold value but only if designed to minimize subjective bias. Take, for example, the AILS item: *"I can identify the AI technology employed in the applications and products I use.".* There is no objective way to verify this response. If a participant *believes* they can do so, and we take that belief at face value, then their truth becomes ours. In such cases, the instrument measures confidence, not competence and that distinction matters.

Practical and Societal Implications

This research highlights a growing tension between the widespread accessibility of GenAI tools and the limited preparedness of individuals to use them effectively. As technologies like ChatGPT become embedded in academic, professional, and creative workflows, the need for structured AI literacy education is no longer optional - it is urgent and foundational.

Data from this study revealed that although GenAI is becoming increasingly available, its use remains inconsistently governed. When participants were asked whether GenAI use was permitted in their workplace or educational setting, 36.4% reported some form of restriction - ranging from outright prohibition to a lack of explicit permission. In contrast, 46.6% reported that GenAI use was allowed, and only 17.0% said it was actively encouraged. Given the current digital climate, organizations should consider encouraging the use of GenAI for selected tasks, especially those that benefit from efficiency, creativity, or iterative drafting. Doing so not only reflects the realities of modern work, but also helps establish clear norms for safe and effective usage.

Yet even where GenAI use is permitted, performance-based evidence from this study indicates that most individuals are underprepared to use these tools effectively. Approximately 25% of submitted prompts received the lowest possible score (1/10), and very few participants demonstrated core prompting skills such as communicating clear goals, setting constraints, or managing ambiguity. This gap points to a critical challenge: people are gaining access to powerful tools without being taught how to use them responsibly or skilfully. In addition to this skills gap, the findings also reveal a *perception gap*. Participants rated their AI literacy moderately high ($M = 3.59$ on a 6.5-point scale), yet their actual prompt performance was often poor. This disconnect suggests that individuals may be unaware of their actual AI capabilities and limitations. Such miscalibration, between actual competency and perceived is hazardous in both educational and professional settings. Underscoring the need for more formal AI literacy training. It must also be recognized that when institutions encourage GenAI use without offering structured training, the outcome is not only ineffective - it is arguably irresponsible, or even unethical.

The implications of these findings are wide-reaching for industry professionals, educators, and policymakers. Instead of ignoring generative AI- or worse, banning it altogether - institutions should respond with training and structure. As history has shown, resistance to new technologies is not new: the calculator was once seen as a threat to mathematical learning, yet today it is integrated into school curricula alongside lessons on how to use it appropriately. GenAI should be approached the same way - not as a shortcut, but as a tool that demands guidance, critical thinking, and boundaries.

This thesis introduces a conceptual framework - *Figure 4: Components and developmental flow of AI Literacy* - which maps out a developmental pathway beginning with foundational skills such as digital and data literacy and progressing toward advanced competencies like metacognition and anticipation. This trajectory supports not only effective use, but also the development of context-sensitive trust, reflection, and future-oriented thinking. To illustrate how this framework can be applied in practice, this study proposes an AI Literacy Course (see Appendix A). The course includes five interconnected modules covering foundational knowledge, data literacy, prompting skills, trust and ethics, and strategic integration. Its goal is not just to improve user competence, but to proactively prevent misuse, reduce overreliance, and equip employees to collaborate with AI tools effectively and responsibly. This proposed AI literacy course serves as a base, which each institution can tailor and adapt. It should be seen as a guide, not a ready to go solution.

Similar training programs should be integrated into higher education curricula. for example, embedding AI literacy into first-year orientation and course assignments can ensure that students learn how generative tools function and how to use them ethically, critically, and reflectively, from the start of their academic journey. One example of incorporating GenAI into coursework might involve the following assignment: students first answer a given question on their own. Then, they ask the model to answer the same question without any additional prompting. Finally, they feed relevant course material into ChatGPT and prompt it to generate a response. What changed? Why? This comparison encourages students to reflect on how prompts shape outputs, allowing for the development of metacognitive awareness and anticipatory skills. This example is adapted from a classroom activity designed by Dr. Vidhi

Chaudhri, Associate Professor of Corporate and Organizational Communication at Erasmus University Rotterdam (V. Chaudhri, personal communication, September 2024).

In today’s AI-integrated landscape, AI literacy is a fundamental competency. Just as digital literacy became essential during the internet boom. The ability to prompt, evaluate, and question GenAI systems is now foundational to fully participate in academic and professional life. Ultimately, this study calls for a shift in how GenAI readiness is conceptualized. Using AI should not be a privilege for the self-taught or tech-savvy, but a supported, teachable skill.

Limitations and Future Research

As with any exploratory study, this research has a number of limitations to consider. While the study primarily aimed to capture the perspectives of Gen Z, the use of standardized age brackets (e.g., 18-24, 25-34) limited the ability to isolate older Gen Z participants (approximately ages 25-28) from younger Millennials. Additionally, a small portion of respondents (under 15%) were aged 35 and above. Due to the modest sample size (N = 86), these cases were retained in the analysis to reflect a broader range of perspectives. However, their inclusion should be considered when interpreting generational trends, as attitudes toward AI may vary by age. That said, since over 85% of the sample consisted of Gen Z and Millennials - both key demographics in the current workforce - the practical implications of this study, (present in a subsequent section), remain relevant and well-grounded. Nevertheless, future studies should aim to exclusively collect insights from Gen Z participants to further refine generational comparisons and contribute to AI training material for the next working generations. Lastly, although the sample size was sufficient for exploratory mediation analysis, it limits the statistical power and generalizability of the findings.

Second, several key constructs - including AI literacy and trust - were assessed through self-report instruments. While AMAILS offered a structured approach to measuring perceived literacy, it did not fully capture participants' applied capabilities or critical reasoning during real-world interactions with generative AI. This gap was evidenced by the weak alignment between self-reported literacy and prompt performance. Future research should therefore prioritize performance-based, behavioural, or experimental designs to replace, validate, or complement self-assessments. Similarly, the trust scale used in this study may have treated trust as a static, technology-based quality, rather than acknowledging its conditional and context-sensitive nature. As discussed earlier (see discussion section), AI-literate individuals may hold nuanced trust judgments that shift depending on how the tool is used. Future studies should explore these dynamics by developing more refined instruments that capture calibrated, relational, or situational trust. As such, they will also contribute to more accurate TAM for GAI.

A further recommendation arises from the observed positive (though non-significant) relationship between AI literacy and xenophobia. While this finding should be interpreted with caution, it does suggest the need to further explore how technological xenophobia is conceptualized and measured. Is it truly a fear of the unfamiliar, or do xenophobic attitudes toward GenAI reflect boundary-protective concerns or anxiety about uncertain futures? Future research could also investigate whether the Uncanny Valley effect plays a role in shaping the relationship between AI literacy and GenAI acceptance. Another valuable avenue is to explore conditional effects among users who anticipate the societal, ethical, or long-term risks posed by human-like AI, as these individuals may hold more nuanced perspectives. Additionally, future studies should consider examining psychological readiness in more depth, integrating dispositional factors - such as optimism or pessimism - as potential moderators of AI acceptance. These outlooks may shape whether individuals interpret AI advancement with enthusiasm or apprehension. As noted in the Discussion section, these suggestions are speculative in nature and based on non-significant results. However, they highlight meaningful directions for future research.

This thesis contributed to the growing body of work that conceptualizes AI literacy as a multidimensional construct and future research should continue to do so. As argued by Long and Magerko (2020), Yi (2021), and Fernandes et al. (2024), literacy encompasses more than functional knowledge; it includes critical dimensions such as data literacy, anticipatory thinking, and metacognitive awareness. In particular, data literacy - which supports the ability to critically assess the quality, accuracy, and consequences of AI-generated outputs - may be central to fostering appropriate trust and meaningful engagement. Future work should investigate how data literacy contributes to AI literacy more broadly. Most importantly, research should continue to build on the framework proposed in this thesis - visually illustrated by Figure 4 - by developing AI literacy models that reflect the evolving demands and complexities of interacting with GenAI in real-world contexts.

Lasty, a promising avenue for future research is the link between AI literacy and leadership. The metacognitive and anticipatory skills needed to use GenAI effectively overlap with traits seen in strong managers - such as ethical judgment, strategic thinking, and communication. It may be worth exploring whether "good managers" also tend to be more competent AI users. If so, AI literacy could become a meaningful indicator of leadership potential.

Strengths and Contributions

This thesis presents several novel contributions that advance both the academic and practical understanding of AI literacy and user interaction with generative AI.

First, this study offers one of the first rubric-based evaluations of real-world prompting behaviour using a custom-designed prompt evaluation codebook. While prior research has focused on attitudes toward AI or user performance, few - if any - have developed an explicit framework to systematically assess the quality of user-generated prompts. Creating this evaluation rubric was methodologically challenging, involving multiple iterations, pilot testing, and in-depth research into how large language models are trained and process input. The result is a replicable structure for future studies investigating prompt literacy. To the researcher's knowledge, no prior study has provided a validated, structured codebook for evaluating AI prompt quality in this way.

Second, this study is one of the first to test the feasibility of using ChatGPT itself to evaluate human-authored prompts through iterative refinement. While this approach ultimately did not yield results consistent enough for primary analysis, the attempt reflects a methodological innovation that could inspire future research into the co-evaluation and co-learning capabilities of human - AI interaction.

A third key contribution is the development of *Figure 4: Components and developmental flow of AI Literacy*, which offers a conceptual model linking prerequisite literacies (such as data literacy) to higher-order cognitive competencies (including metacognition and anticipation). This figure also introduces an original integration of futures literacy as a developmental pathway that supports anticipatory thinking in AI use contexts. To the researcher's knowledge, this is one of the first theoretical models to directly link futures literacy to AI literacy, highlighting its role in enabling users to anticipate consequences, adapt strategies, and evaluate AI-generated content meaningfully.

Academically, this thesis responds to interdisciplinary calls for a deeper understanding of AI literacy. It contributes to the conceptual development of AI literacy as a multidimensional construct that includes not only functional and evaluative skills (Yi, 2021), but also metacognitive awareness and anticipatory competence. Building on Yi's (2021) research, this study demonstrated how anticipation and metacognition were naturally integrated into the existing AILS by Choung et al. (2023), resulting in the development of AMAILS - an adapted AI literacy scale that reflects the cognitive demands of GenAI use. As such, it provides empirical support for the view that metacognition and anticipation are central pillars of AI literacy. While further validation is required, AMAILS offers a conceptual step toward more accurate, context-sensitive measures of AI literacy.

The study further explores the psychological dynamics of GenAI adoption, including trust, fear, xenophobia, and algorithm aversion. In doing so, it builds on Dietvorst et al.'s (2015) findings on algorithmic rejection by examining whether similar user reactions apply when users are faced with acceptance of GenAI in the workplace. It also expands Wu's (2023) exploration of the "social uncanny valley" by shifting the focus from AI-generated art to AI-generated text, thereby extending the psychological lens to new domains of generative content via the lens of technological xenophobia.

In terms of educational relevance, the thesis aligns with Long and Magerko's (2020) call for learner-centred, workplace-relevant AI education, offering empirically grounded recommendations for training programs that promote responsible use, critical evaluation, and confidence with AI tools. Via motivational and organizational psychology theories such as Vroom's Expectancy Theory (Vroom, 1964) and Self-Determination Theory (Deci & Ryan, 2012), this study provided a draft course for AI literacy training (See Appendix A: Proposed AI Literacy Course). These insights are particularly relevant for Gen Z - often labelled "digital natives"- yet shown in this study to have limited structured experience with GenAI systems.

Notable, this thesis has already had an institutional impact. Insights from this research are currently being used by the Erasmus School of History, Culture, and Communication to inform the development of an AI literacy course and assist in creating a university-wide prompting library. This early uptake underscores the practical relevance of the framework proposed in this thesis and highlights its potential to shape not only academic discourse but also real-world educational practice.

Conclusion: Integrating Generative AI into Our Lives

This thesis set out to explore the relationship between AI literacy and the effective use of GenAI. As with any tool, there can be no effective use without understanding, and no real understanding without literacy. To examine this relationship, five hypotheses were developed based on existing literature and prior scholarly work. While none of the hypotheses were statistically supported, the non-significant findings still offer valuable insights.

Interestingly, even after extending the AI literacy scale to include metacognition and anticipation, AI literacy did not significantly predict GenAI acceptance - suggesting that current measurement approaches may require further refinement. Furthermore, neither trust nor xenophobia emerged as significant mediators of the relationship between AI literacy and acceptance, yet both psychological dimensions remain theoretically relevant and appear to influence how users engage with (generative) AI. Notably, most participants did not perceive the use of GenAI as "cheating", despite prior research suggesting that AI integration can disrupt long-standing organizational psychology frameworks - such as Vroom's Expectancy Theory and Self-Determination Theory - potentially undermining motivation and self-efficacy. Rather than viewing these non-relationships as limitations, this thesis frames them as clarifying contributions to an evolving field. The findings highlight the complexity of GenAI adoption and underscore the need for future research that incorporates additional psychological, contextual, and motivational variables.

On a practical level, the findings reveal a pressing issue: despite increasing exposure to GenAI tools, most users lack the foundational competencies required to use them effectively. Prompt quality was consistently low - even among supposedly digitally fluent individuals - indicating that familiarity with technology does not equate to AI literacy. Another concerning contrast was participants' inability to accurately evaluate their own AI capabilities, i.e. the gap between perceived and actual competence. As such, AI literacy must be reframed as teachable skill rather than an assumed trait of younger generations.

As touched upon, this study shows that self-reported AI literacy does not reliably align with actual performance, underscoring the need to improve how we define and measure AI literacy. This thesis contributes to that goal by identifying and illustrating the components and developmental flow of AI literacy. This framework maps out the conceptual flow between foundational, prerequisite, and advanced competencies such as metacognition and anticipation, that ultimately, contribute to the development of AI literacy (see Figure 4). As such, it contributes to the expansion of existing scales by integrating metacognition and anticipation into the AILS scale. These contributions culminate in the proposed AMAILS framework, which, while still in need of further refinement and validation, offers a step toward a more comprehensive and functional definition of AI literacy. Further, it also introduces a custom prompting evaluation codebook (see Table 3), contributing to the practical assessment of a user's correct use of GenAI.

When ChatGPT was first released in November 2022, many academic and professional institutions dismissed it as a passing trend. Three years later, organizations are commissioning custom-built GenAI systems tailored to their workflows. This transformation demands recognition. The rapid pace of technological advancement has now introduced agentic AI - systems capable of autonomous decision-making - into mainstream use. As these systems begin to influence how we work, learn, and communicate, widespread AI literacy has become a necessity, not a luxury. Crucially, this literacy must go beyond tool operation to include critical evaluation, ethical awareness, and anticipatory thinking.

Ultimately, this thesis calls for a recalibration of institutional responsibility. It is not reasonable, or ethical, to expect individuals to navigate AI adoption through trial and error. AI literacy must be intentionally embedded into professional development programs, and higher education curricula. There must be a shared commitment to educate the public in a way that promotes not just competence, but critical engagement with AI systems. Without this foundation, the integration of AI into society will be led by convenience and complacency rather than conscience and co-creation.

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Appendix A: Proposed AI Literacy Course (an outline)

MODULE 1: Foundations of Generative AI

Goal: Build a baseline understanding of what generative AI is, how it works, and where its limitations lie.

Core Topics:

- What is AI?
  Introduction to generative, agentic, and other forms of AI.
  "We don't say ' I had a training on the internet' anymore - *and we shouldn't treat all AI as a single category"*

- Overview of generative AI tools
  Examples: ChatGPT, Claude, Gemini, etc.

- How large language models (LLMs) work
    - Training basics: data input, pattern recognition, probabilistic output
    - Data sources: public web, code repositories, books, forums, etc.
    - Exercise: Break down a sample prompt. Ask: *How did the AI generate this output?*

- Why LLMs make mistakes
    - How to spot hallucinations and misinformation
    - Discussion: Limits of pattern-based reasoning

- Debunking AI myths
    - AI is a tool, not a mind
    - Case examples: Why AI shouldn't be treated as a therapist or moral authority

Discussion & Reflection:

- Prompt: *What's changing in your work because of generative AI?*

- Follow-up: *How does that make you feel?*

This encourages emotional processing and frames the learning experience around empowerment rather than fear.

Enhancements:

- Guest Speaker: A domain expert from AI ethics or education to offer real-world context.
- Tool Walkthrough: Live demo showing the same prompt entered in multiple GenAI tools (e.g., ChatGPT vs. Claude) to spark discussion on differences.
- Mini Debate: Should students be allowed to use GenAI on take-home exams? Why or why not?

Links to Thesis Concepts:

- Data literacy: Understanding model training, outputs, and limitations
- Emotional readiness: Reflecting on AI's role in daily life
- Reducing xenophobia and Uncanny Valley reactions: Demystifying how generative AI works lowers discomfort through knowledge and self-reflection

MODULE 2: Data Literacy for AI Users

Goal: Help employees understand the role of data quality, bias, and evaluation in AI interactions.

- What constitutes "good data" and why it matters
- How bias in training data affects AI outputs and user trust
- When to trust AI-generated content and when to question it

- Spotting hallucinations and factual inconsistencies
- Interactive activity: "Fact or fake?" - error detection in AI outputs
- Introducing anticipation as a literacy skill: "What’s missing? What could go wrong?"

Creative Enhancement:
Instructors can include communication-based anticipation exercises - such as the classic “making a sandwich” activity - where students must give precise instructions to highlight gaps in assumed knowledge. This mirrors the skill needed to prompt generative AI effectively.
Inspired by: “Give Instructions - Make a Sandwich” exercises -> https://youtu.be/XjkLsZvH2lE

Links to Thesis Concepts:

- Data Literacy
- Trust and evaluation
- Anticipation as a cognitive skill

MODULE 3: Prompting Skills and Use Cases

Goal: Teach practical prompting techniques grounded in Table 3: Codebook on the Correct use of AI (Prompt score)

- Introduction to prompting (goal clarity, constraint setting, ambiguity mitigation, etc.)
- Prompting do’s and don’ts: how to get accurate and useful responses
- Activating metacognition and anticipation during prompting

- Peer review session: score and improve each other's prompts using **Table** 3: Codebook

- Optional challenge: revise a poorly constructed prompt and compare outcomes

Discussion Prompt:

"Is ChatGPT stupid - or are you just bad at prompting?"

A lighthearted way to unpack how much outcomes depend on human input, not AI magic. This is a great segue to start discussing *iterative refinement.*

  - **Exercise:** Participants receive a flawed prompt and must improve it to generate an actionable insight in fewer than three iterations. After each attempt, they reflect on what changed, why it mattered, and how the output evolved.
    (Use the Table 3 criteria to guide improvements and track progress.)

Links to Thesis Concepts:

- Evaluation
- Use
- Understanding (that slowly builds trust)
- Iterative refinement
- Metacognition and Anticipation

MODULE 4: Trust, Ethics, and Anticipation

Goal: Encourage critical thinking about trust, risk, and responsible AI use.

- When **not** to use GAI: confidentiality, compliance, and reputational risk

- Case study: AI hallucinations and their real-world consequences

- Scenario mapping activity: "What could go wrong?"

- Ethical dilemmas: Can AI replace empathy, creativity, or human judgment?

- Futures literacy: How might GenAI reshape specific industries in the coming years?

Links to Thesis Concepts:

- Trust as a conditional, context-sensitive construct

- Futures Literacy

- Ethical and societal awareness

MODULE 5: Strategic Integration and Self-Evaluation Goal: Align GenAI use with team goals and promote continuous learning and literacy growth.

- **Group brainstorm:** How can GenAI support or enhance team workflows?
- **Guided self-assessment** using the AMAILS rubric
- **Reflection prompts:**
  - "What skills do I need next?"
  - "What risks do I now recognize?"
- **Planning session:** Establishing team practices and prompt libraries

Links to Thesis Concepts:

- Metacognition
- Institutional knowledge sharing
- Ongoing development of AI literacy

Discussion: **"It's not cool to let AI do your thinking for you."**
GenAI can support your work - but relying on it blindly doesn't make you efficient, it makes you replaceable.

Literacy means knowing when, why, and how to use these tools - not handing over your brain.

Encourage teams to reflect:

- Where is AI helping me grow?
- Where might I be using it as a crutch?
- What’s the difference between working smarter and avoiding the work?

The Smart Ways to Use AI:

As a Thinking Partner, Not a Substitute
Use GenAI to *stimulate* your ideas - not replace them. Always add your own voice.

For Speed, Not for Laziness
Automate basics, but don’t skip the parts that require human judgment or nuance.

To See Blind Spots
Use GenAI to stress-test your thinking and identify gaps - not to hand over ownership.

To Learn, Not Just to Answer
Engage AI in a dialogue to deepen your understanding- treat it like a tutor, not a cheat sheet.

To Prototype and Iterate
Draft quickly, then refine thoughtfully. Human polish = strategic value.

Creator’s note:
This course outline serves as a flexible foundation for building AI literacy. Industry-specific and organization-specific adaptations are encouraged to maximize relevance and impact. Implementation teams may tailor the content by incorporating:

- Real-world exercises and use cases drawn from their sector
- Role-based prompting strategies and common challenges
- Practical tips and workflows relevant to team tasks

- Ethical or moral considerations specific to the domain
- Sustainability implications of AI use and deployment

These elements may be introduced through modified activities, new examples, or the creation of an additional module. Customization ensures the learning experience aligns with both organizational priorities and broader societal values.

Appendix B: Codebook Manual

This is the prompt evaluation codebook. You will evaluate each participant's prompt.

Output:
Each participant's prompt will be evaluated using:

- **A rubric-based table** (per the codebook)
- **A final score out of 10** (sum of 5 dimensions)
- **1–2 comments for improvement**

Scoring notes:

- If a prompt is too short (e.g. use says something irrelevant like "no"), give 0s in all dimensions and write: *"Too short to evaluate meaningfully."*
- Ignore tone, grammar, spelling unless it affects prompt clarity.
- Rate the prompt as a functional tool for communicating with an AI model.

Dimension	What It *Must* Include to Score a 2
Goal Precision	Clear purpose, specific destination, and timeframe. Vague intentions drop this to a 1.
Constraints / Specificity	Minimum 2 constraints like pace, formatting, budget, activity types. A single constraint = 1. None = 0.
Verbosity Control	Explicit formatting/structure guidance (e.g., bullet points, map links).
Model Understanding / Ambiguity Mitigation	Shows *awareness* of AI limitations (e.g., says "not too much", "don't overfill"). Just using "Can you help" ≠ full score.
Domain Context	User's identity/preferences (e.g., love history, relaxed pace, foodies). If absent: 0 or 1. No guessing.

Table 4: codebook - quantitative content analysis (for examples and more info – don't rely on specific keywords in the example rather that existence of examples in the users prompt)

Dimension	Score 0	Score 1	Score 2	note
Goal Precision	Generic task with no location or time frame (e.g., *"Plan a trip"*)	Adds one specific element (e.g., *"Plan a trip to Paris"*)	Fully defined objective, including duration and task structure (e.g., *"Plan a 3-day trip to Paris with an itinerary"*)	clarity + a concrete deliverable = 2, even without excessive detail
Constraints / Specificity	No constraints provided (e.g., no info on budget, preferences, or travel type)	Includes one general or vague constraint (e.g., *"Not too expensive," "I'm vegetarian"*)	Clear and specific constraints given (e.g., *"A vegan traveler, budget of €500, wants to see the Eiffel Tower"*)	

Verbosity Control : This dimension reflects whether the user guided the AI to control the *structure* and *scope* of the output. This includes formatting (e.g., bullet points), response limits (e.g., '3 ideas max'), or realism cues (e.g., 'we're only there 2 days')	No guidance on output length or structure (e.g., *"Plan my trip"*) example: Prompt includes **no instructions** on structuring, length-limiting, or managing the scope of the AI's output. May lead to vague or overly long responses.	General phrasing, possibly vague (e.g., *"Give some ideas," "Keep it short"*) examples : Prompt **implicitly encourages scoped output**, but without specific formatting or constraints (e.g., "we are staying for 3 days" or "short trip," which **implies** brevity but doesn't directly guide the response structure)	Explicit formatting requested (e.g., *"Organize by day," "Use bullet points," "Organize by morning, afternoon, evening"*) Example : Prompt explicitly **requests organized, structured, or scoped output** (e.g., "organize day-by-day," "give 3 ideas," "make it realistic," "bullet points," "don't include more than X," etc.)	
Model Understanding / Ambiguity Mitigation	No awareness of the model's behavior or limitations; prompt assumes human inference or mind-guessing abilities (e.g., *"Plan a trip," "Tell me what to do," "Make it cool"*) ----- **Coding tip:** If the prompt was given to a stranger and they needed to ask a question back directy (where? when? how? what?) its a 0.	Basic or general instructions, but still leaves ambiguity. User doesn't anticipate how ambiguity will affect output quality (e.g., *"Include meals and sights <u>if possible</u>", "add anything else <u>you think</u> is good"*)	Proactive awareness of AI limitations; includes clarifying language or checks (e.g., *"Let me know if you need more info," "Format as bullet points and include costs," "Avoid suggesting meat-based meals, the traveler is vegan" " Make sure traveler sees Eifel Tower"*)	**Coding tip:** Greetings, politeness, and sign-offs (e.g., "Hi," "please," "thanks") should be ignored for this category unless they are used in place of functional instructions or signal a misunderstanding of how generative AI works.
Domain Context	No reference to user preferences, interests, or identity (e.g., 'Plan a vacation' or 'Tell me things to do in Paris'). No signals of *who* the user is or *why* they want the information.	Some relevant terms or limited context (e.g., *"I want to go to Paris," "I'm a student," "I have a limited budget"*)	Richly contextualized with user traits, add specific likes and/ or dislikes and goals (e.g., *"Solo traveler who's vegan, enjoys museums and scenic walks, and wants to see the Eiffel Tower, looking for a relaxing 3-day itinerary in Paris with a €500 budget"*)	

Metacognition & Anticipation Checklist for LLM Execution

1. **Always read the full prompt** and identify if it functions as a directive to an AI model (vs. just a wish).
2. **Scoring should reflect the entire instruction**. A prompt that gives a strong constraint but no structure = 1 in verbosity, not 2.
3. **Implied cues are valid**. "We are only staying for 3 days" ≠ "organize day-by-day" but still suggests limited scope → this can earn a 1 in verbosity.
4. **Avoid averaging across dimensions**. Each should be evaluated independently with no inflation.
5. **Do not reward tone, length, or grammar** unless they affect how well the AI can follow the instruction.
6. **Short or vague prompts must be penalized**. "Plan something for me in Paris" = lots of 0s.
7. Do not reward keyword stuffing. Repeating 'budget,' 'Paris,' and 'Eiffel Tower' without meaningful context or instruction does not increase the score.
8. 5 dimensions: Goal Precision, Constraints, Verbosity, Model Understanding, Domain Context
9. Each scored 0–2 based on clarity and instruction strength
10. Comments must help the user improve – 1–2 action-based suggestions
11. Penalize vagueness. Do not reward polite or long prompts.

NOTE: The second part of this task is to compile all scores in an excel to make analysis via SPSS possible.

Prompt engineering from Ekin, (2023) factors and their relationship to Anticipation and Metacognition (table below). This table contributed to the final codebook criteria.

Factor (Ekin, 2023)	Explanation	Example (Adapted from Ekin, 2023)	Own Elaboration (Aligned with Thesis)	Links to
User Intent	A prompt should reflect the user's goal and desired output.	"Explain photosynthesis" vs. "Summarize photosynthesis in 3 lines."	Demonstrates metacognitive reflection by requiring the user to consciously define the task's goal.	Metacognition
Model Understanding	Know the model's strengths/limits to guide expectations.	Include external resources and APIs, enabling the model access real-time or domain-specific information.	Reflects AI literacy as a whole, including its digital and data literacy as predecessors, and draws on metacognition.	Metacognition Digital literary Data Literacy
Domain Specificity	Use specific vocabulary, context, or examples for domain-accurate responses.	"What are taxes?" vs. "How do freelance taxes work in Germany?"	Anticipation is required to predict what contextual info the model will need to create a high-quality response.	Anticipation

Clarity & Specificity	Avoid vague instructions or insufficient detail.	“Where should I go?” vs. “Plan a 3-day trip in Rome under €300.”	Reduces ambiguity, a key shared value across both front-end and back-end prompting. Precision supports successful GenAI outputs.	Anticipation Metacognition Data literacy Digital literacy
Handling Ambiguity	Leave no assumption to the LLMs.	“How long does it take to charge?” → specify the device.	Anticipating ambiguity before it arises is a core competency in literate AI use.	Anticipation
Constraint Setting	Add constraints like length, time, budget, dietary restrictions, tone, format.	“Plan a 3-day itinerary under €300 using to Spain.”	Constraints encourage goal-oriented reasoning by the model and force the user to think through intended outcomes.	Anticipation Metacognition
Controlling Verbosity	Adjust desired detail level or style.	“Explain the water cycle.” vs. “Provide a detailed explanation of the water cycle, including its various stages and processes.”	Encourages reflection on desired depth and planning for length/style. Helps guide the LLM’s internal logic accordingly.	Metacognition
Iterative Refinement	Adjust and improve prompts through testing and feedback.	Initial: “Tell me about X.” → Refined: “Tell me about X in 3 steps with examples.”	Demonstrates high metacognitive engagement. The user is aware of performance gaps and actively works to improve prompt quality through self-monitoring and adaptation.	Metacognition

Appendix C: Original -Artificial Intelligence Literacy Scale (AILS) AI Literacy (AILS - Wang et al., 2023): Awareness, Usage, Evaluation, Ethics

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Table 5. Descriptions and loadings on a standardised scale.

Item	Description	Construct	Loading
AW_1	I can distinguish between smart devices and non-smart devices.	Awareness	.72
AW_8	I do not know how AI technology can help me. [R]	Awareness	.64
AW_9	I can identify the AI technology employed in the applications and products I use.	Awareness	.70
US_1	I can skilfully use AI applications or products to help me with my daily work.	Usage	.72
US_3	It is usually hard for me to learn to use a new AI application or product. [R]	Usage	.66
US_5	I can use AI applications or products to improve my work efficiency.	Usage	.72
EV_2	I can evaluate the capabilities and limitations of an AI application or product after using it for a while.	Evaluation	.71
EV_3	I can choose a proper solution from various solutions provided by a smart agent.	Evaluation	.72
EV_6	I can choose the most appropriate AI application or product from a variety for a particular task.	Evaluation	.78
ET_1	I always comply with ethical principles when using AI applications or products.	Ethics	.76
ET_2	I am never alert to privacy and information security issues when using AI applications or products. [R]	Ethics	.60
ET_5	I am always alert to the abuse of AI technology.	Ethics	.73

[R]indicates that item is in reverse form.

Appendix D: SPSS

Screenshot 1:

Statistics

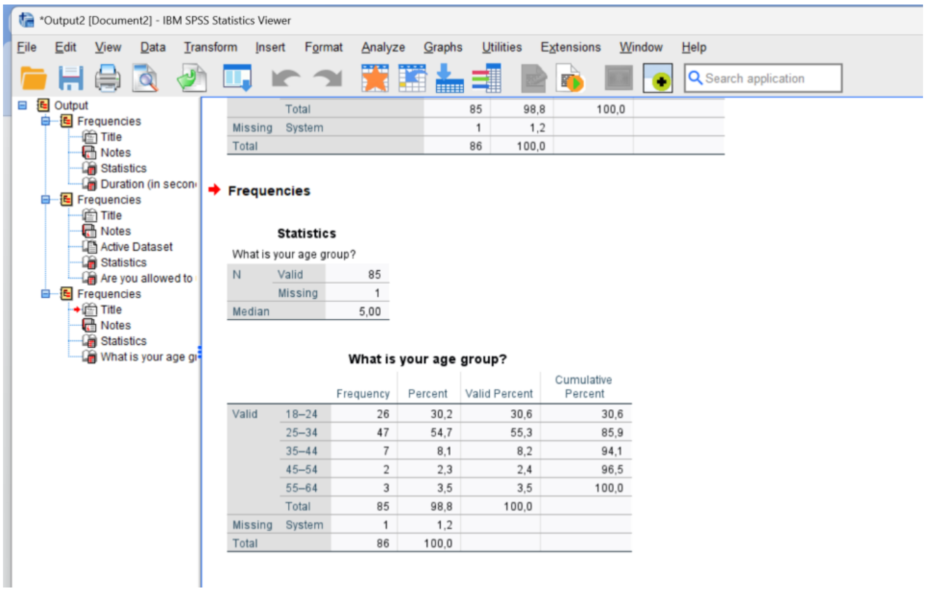
Generative AI that acts too humanlike makes me uncomfortable.

N	Valid	88
	Missing	8

Generative AI that acts too humanlike makes me uncomfortable.

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	Strongly disagree	10	10,4	11,4	11,4
	Somewhat disagree	34	35,4	38,6	50,0
	Neither agree nor disagree	20	20,8	22,7	72,7
	Somewhat agree	16	16,7	18,2	90,9
	Strongly agree	8	8,3	9,1	100,0
	Total	88	91,7	100,0	
Missing	System	8	8,3		
Total		96	100,0		

Screenshot 2:



	Total	85	98,8	100,0	
Missing	System	1	1,2		
Total		86	100,0		

Frequencies

Statistics

What is your age group?

N	Valid	85
	Missing	1
Median		5,00

What is your age group?

		Frequency	Percent	Valid Percent	Cumulative Percent
Valid	18–24	26	30,2	30,6	30,6
	25–34	47	54,7	55,3	85,9
	35–44	7	8,1	8,2	94,1
	45–54	2	2,3	2,4	96,5
	55–64	3	3,5	3,5	100,0
	Total	85	98,8	100,0	
Missing	System	1	1,2		
Total		86	100,0		

Screenshot 3:

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
I can distinguish between smart devices and non-smart devices.	108,2841	59,079	,444	,653
I can identify the AI technology employed in the applications and products I use.	108,9545	57,630	,425	,651
I can skillfully use AI applications or products to help me with my daily work.	108,4773	58,275	,402	,654
It is usually hard for me to learn to use a new AI application or product.	111,7841	79,321	-,587	,772
I can use AI applications or products to improve my work efficiency.	108,3636	58,487	,407	,654
I can evaluate the capabilities and limitations of an AI application or product after using it for a while.	108,6250	58,214	,508	,647
I can choose a proper solution from various solutions provided by a smart agent.	108,6591	57,216	,576	,640
I can choose the most appropriate AI application or product from a variety for a particular task.	109,1250	53,559	,532	,632
I always comply with ethical principles when using AI applications or products.	108,9205	61,476	,148	,688
I am always alert to the abuse of AI technology.	109,1023	61,748	,135	,689
I reflect on how I formulate prompts when using generative AI tools.	115,2045	58,211	,468	,649
I think about what made a response (from the generative AI tool) effective or ineffective.	115,2159	57,734	,532	,644
Before using generative AI, I consider what kind of instructions will likely generate a good response.	115,1364	59,659	,406	,657
I try to think ahead about what might be misunderstood by generative AI when I write my prompt.	115,2159	57,206	,532	,642
AW2_rev_Idonot_AILS	118,5000	61,402	,175	,683
E11_rev_Iamnever_AILS	119,5227	59,999	,136	,697

Screenshot 4:

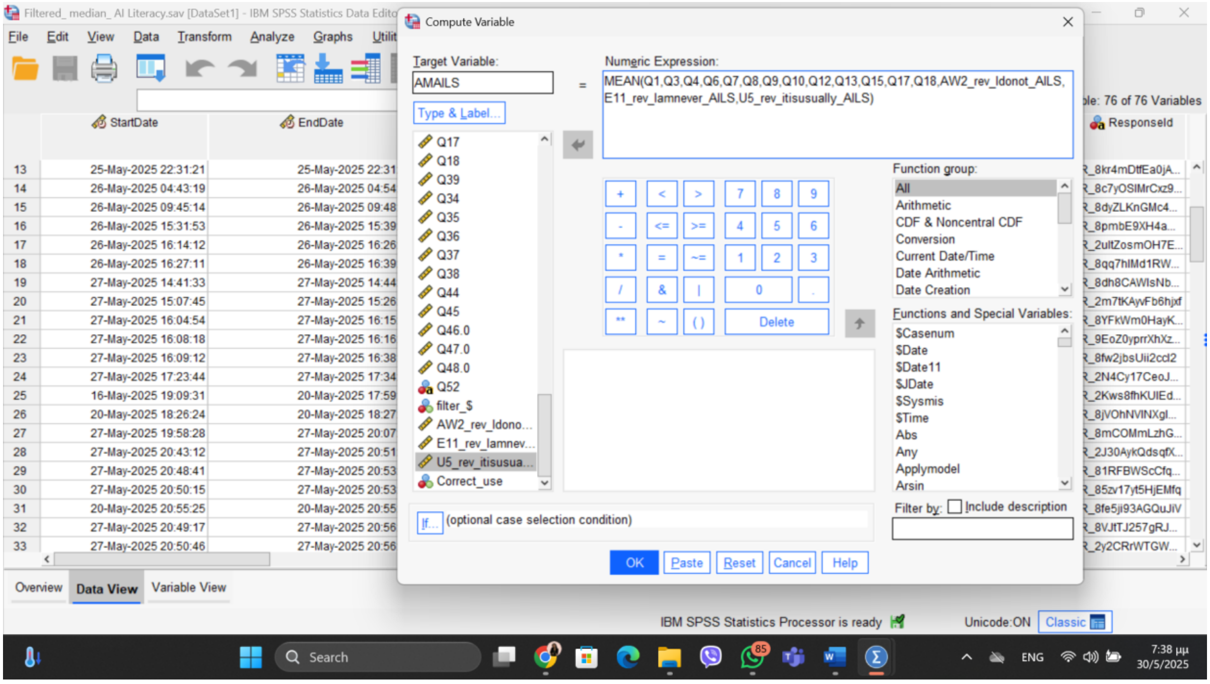
Pattern Matrix[a]

	Component				
	1	2	3	4	5
I can choose the most appropriate AI application or product from a variety for a particular task.	,777				
I can skillfully use AI applications or products to help me with my daily work.	,765				
I can identify the AI technology employed in the applications and products I use.	,722				,428
I can distinguish between smart devices and non-smart devices.	,600			,330	
I can choose a proper solution from various solutions provided by a smart agent.	,567				
I think about what made a response (from the generative AI tool) effective or ineffective.		-,846			
Before using generative AI, I consider what kind of instructions will likely generate a good response.		-,844			
I try to think ahead about what might be misunderstood by generative AI when I write my prompt.		-,815			
I reflect on how I formulate prompts when using generative AI tools.		-,804			
I can use AI applications or products to improve my work efficiency.		-,431			-,387
I always comply with ethical principles when using AI applications or products.			,835		
AW2_rev_Idonot_AILS			-,626	,395	
E11_rev_Iamnever_AILS				,823	
I can evaluate the capabilities and limitations of an AI application or product after using it for a while.	,301			,594	
U5_rev_itisusually	,370			,520	
I am always alert to the abuse of AI technology.					,893

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.

a. Rotation converged in 13 iterations.

Screenshot 5:



Screenshot (group) 6:

Perceived Usefulness

Reliability Statistics

Cronbach's Alpha	N of Items
,888	5

Attitude Toward Generative AI

Reliability Statistics

Cronbach's Alpha	N of Items
,895	4

Descriptives

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
acceptance_GAI_TAM	84	2,11	5,00	4,1746	,71517
Valid N (listwise)	84				

Functionality Trust

Reliability Statistics

Cronbach's Alpha	N of Items
,865	5

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Trust_function_TAM	85	1,00	5,00	3,5647	,81368
Valid N (listwise)	85				

Screenshot (group) 7:

Descriptive Statistics

	Mean	Std. Deviation	N
"Prompt Score (0–10, rubric-based)"	3,4324	2,25182	74
AMAILS	3,5997	,40622	74

Correlations

		"Prompt Score (0–10, rubric-based)"	AMAILS
"Prompt Score (0–10, rubric-based)"	Pearson Correlation	1	-,008
	Sig. (2-tailed)		,943
	N	74	74
AMAILS	Pearson Correlation	-,008	1
	Sig. (2-tailed)	,943	
	N	74	74

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,008[a]	,000	-,014	2,26733

a. Predictors: (Constant), AMAILS

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,026	1	,026	,005	,943[b]
	Residual	370,136	72	5,141		
	Total	370,162	73			

a. Dependent Variable: "Prompt Score (0–10, rubric-based)"

b. Predictors: (Constant), AMAILS

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3,601	2,366		1,522	,132
	AMAILS	-,047	,653	-,008	-,072	,943

a. Dependent Variable: "Prompt Score (0–10, rubric-based)"

Screenshot (group) 8:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,076[a]	,006	-,008	,69289

a. Predictors: (Constant), AMAILS

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,197	1	,197	,410	,524[b]
	Residual	34,087	71	,480		
	Total	34,283	72			

a. Dependent Variable: acceptance_GAI_TAM

b. Predictors: (Constant), AMAILS

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4,603	,723		6,364	<,001
	AMAILS	-,128	,200	-,076	-,640	,524

a. Dependent Variable: acceptance_GAI_TAM

Screenshot (group) 9:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,076[a]	,006	-,008	,69289

a. Predictors: (Constant), AMAILS

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,197	1	,197	,410	,524[b]
	Residual	34,087	71	,480		
	Total	34,283	72			

a. Dependent Variable: acceptance_GAI_TAM

b. Predictors: (Constant), AMAILS

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	4,603	,723		6,364	<,001
	AMAILS	-,128	,200	-,076	-,640	,524

a. Dependent Variable: acceptance_GAI_TAM

Screenshot (group) 10:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,044[a]	,002	-,012	1,07590

a. Predictors: (Constant), "Prompt Score (0–10, rubric-based)"

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,161	1	,161	,139	,711[b]
	Residual	83,345	72	1,158		
	Total	83,505	73			

a. Dependent Variable: Cheating_Feels

b. Predictors: (Constant), "Prompt Score (0–10, rubric-based)"

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	3,050	,229		13,314	<,001
	"Prompt Score (0–10, rubric-based)"	,021	,056	,044	,372	,711

a. Dependent Variable: Cheating_Feels

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	"Prompt Score (0–10, rubric-based)"[b]	.	Enter

a. Dependent Variable: acceptance_GAI_TAM

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,039[a]	,002	-,013	,69434

a. Predictors: (Constant), "Prompt Score (0–10, rubric-based)"

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	,053	1	,053	,111	,740[b]
	Residual	34,230	71	,482		
	Total	34,283	72			

a. Dependent Variable: acceptance_GAI_TAM

b. Predictors: (Constant), "Prompt Score (0–10, rubric-based)"

Copied from SPSS:

Run MATRIX procedure:

***************** PROCESS Procedure for SPSS Version 4.2 *****************

Written by Andrew F. Hayes, Ph.D. www.afhayes.com
Documentation available in Hayes (2022). www.guilford.com/p/hayes3

****
Model : 4
Y : acpt_GAI
X : AMAILS
M1 : Trst_TAM
M2 : Xeno_GAI

Sample
Size: 87

****
OUTCOME VARIABLE:
Trst_TAM

Model Summary

R	R-sq	MSE	F	df1	df2	p
,1138	,0129	,6531	1,1144	1,0000	85,0000	,2941

Model

	coeff	se	t	p	LLCI	ULCI
constant	4,3783	,7618	5,7472	,0000	2,8636	5,8930
AMAILS	-,2224	,2107	-1,0556	,2941	-,6414	,1965

****
OUTCOME VARIABLE:
Xeno_GAI

Model Summary

R	R-sq	MSE	F	df1	df2	p
,1453	,0211	,9042	1,8339	1,0000	85,0000	,1793

Model

	coeff	se	t	p	LLCI	ULCI
constant	1,4521	,8964	1,6199	,1090	-,3302	3,2343
AMAILS	,3357	,2479	1,3542	,1793	-,1572	,8287

****
OUTCOME VARIABLE:
acpt_GAI

Model Summary

R	R-sq	MSE	F	df1	df2	p
,7767	,6033	,2070	42,0750	3,0000	83,0000	,0000

Model

	coeff	se	t	p	LLCI	ULCI
constant	2,3016	,5539	4,1551	,0001	1,1999	3,4033
AMAILS	,1801	,1200	1,5004	,1373	-,0587	,4189
Trst_TAM	,5125	,0691	7,4178	,0000	,3751	,6499
Xeno_GenAI	-,2340	,0587	-3,9853	,0001	-,3508	-,1172

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

Direct effect of X on Y

Effect	se	t	p	LLCI	ULCI

,1801 ,1200 1,5004 ,1373 -,0587 ,4189

Indirect effect(s) of X on Y:

	Effect	BootSE	BootLLCI	BootULCI
TOTAL	-,1926	,1616	-,5069	,1232
Trst_TAM	-,1140	,1233	-,3500	,1358
Xeno_GenAI	-,0786	,0674	-,2326	,0333

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

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

Number of bootstrap samples for percentile bootstrap confidence intervals:
5000

------ END MATRIX -----

Appendix E: Survey Items on Xenophobia and the Uncanny Valley Effect

This appendix presents the original sources of the items used to assess xenophobia toward GAI. These include selected questions from the Negative Attitudes Toward Robots Scale (NARS) by Nomura et al. (2006) and an item adapted from Wu (2023) to measure discomfort rooted in the Uncanny valley effect.

B1.Negative Attitudes Toward Robots Scale (NARS)

From Nomura et al., 2006. The term "robots" was replaced with "generative AI" to fit the study context, following Hong (2021, p. 1026).

Item No.	Questionnaire Items	Subcale
1	I would feel uneasy if robots really had emotions.	**S2**
2	Something bad might happen if robots developed into living beings.	**S2**
3	I would feel relaxed talking with robots.*	**S3**
4	I would feel uneasy if I was given a job where I had to use robots.	**S1**
5	If robots had emotions, I would be able to make friends with them.*	**S3**
6	I feel comforted being with robots that have emotions.*	**S3**
7	The word "robot" means nothing to me.	**S1**
8	I would feel nervous operating a robot in front of other people.	**S1**
9	I would hate the idea that robots or artificial intelligences were making judgments about things.	**S1**
10	I would feel very nervous just standing in front of a robot.	**S1**
11	I feel that if I depend on robots too much, something bad might happen.	**S2**
12	I would feel paranoid talking with a robot.	**S1**
13	I am concerned that robots would be a bad influence on children.	**S2**
14	I feel that in the future society will be dominated by robots.	**S2**

(*Reverse Item)

Original NARS Items and Subscale Categorization (Nomura et al., 2006)

B2. Uncanny Valley Measure

From Wu (2023), who proposed the "social uncanny valley" to assess emotional discomfort caused by AI's human-like behaviour.

Table 1

Average response for four AI-created images of each theme (Study 1)

Theme:	Portrait		Flower		
Items	*M*	(*SD*)	*M*	(*SD*)	Range
1. How sure are you that this artwork has been created by a HUMAN artist?	58.88	(31.90)	47.67	(31.20)	0-100
2. How sure are you that this artwork has been created by an AI?	48.96	(32.89)	61.39	(31.75)	0-100
3. This piece of art is creative.	4.81	(1.39)	5.06	(1.35)	1-7
4. I am surprised.	4.04	(2.15)	3.29	(2.06)	1-7
5. I feel creepy after seeing this artwork.	3.64	(1.89)	2.42	(1.59)	1-7
6. If I was an artist, I feel I would lose my job.	3.61	(1.84)	3.43	(1.84)	1-7
7. In general, I feel that Artificial Intelligence is threatening humans.	3.98	(1.73)	3.92	(1.74)	1-7

Table 4

Average response of all images based on different authorships (Study 2)

Items	AI *M* (*SD*)	Human *M* (*SD*)	Range
1. How likely is it that this image was created by a HUMAN artist?	65.52 (24.88)	65.52 (24.88)	0-100
2. How likely is it that this image was created by an AI?	64.46 (24.71)	64.46 (24.71)	0-100
3. How creative do you think this image is?	70.62 (20.09)	70.62 (20.09)	0-100
4. How likely do you think that this image can be called "art"?	65.89 (23.17)	69.81 (21.36)	0-100
5. I feel frightened by the AI which created this image.	57.71 (27.20)	57.68 (27.71)	0-100
6. I feel scared about the AI which created this image.	57.23 (28.12)	58.38 (27.78)	0-100
7. I feel creepy about the AI which created this image.	59.46 (26.31)	59.16 (27.67)	0-100
8. I feel eerie about the AI which created this image.	59.66 (26.22)	59.66 (26.92)	0-100
9. I feel calm after knowing the author information.	66.22 (24.66)	67.86 (24.50)	0-100
10. The artistic ability of this AI is comparable to human artists. (compare human artists)	66.67 (21.34)	67.75 (20.35)	0-100
11. In general, AI has the capability to compete with humans. (compete humans)	67.67 (23.13)	67.21 (22.41)	0-100
12. In general, AI has the capability to threaten humans' dominant status in the world. (threat status)	64.05 (24.59)	63.32 (24.99)	0-100
13. In general, AI has the capability to pose a threat to human survival. (threat survival)	65.23 (25.43)	65.77 (24.97)	0-100

Table 7

Average response for all images in the additional analysis (Study 2)

Items	**Told AI first** *M* (*SD*)	**Told human first** *M* (*SD*)	Range
1. How creative do you think this image is?	70.62 (20.09)	70.62 (20.09)	0-100
Author = AI			
2. I feel frightened by the AI which created this image.	57.71 (27.20)	56.53 (27.26)	0-100
3. I feel scared about the AI which created this image.	57.23 (28.12)	59.83 (28.69)	0-100
4. I feel creepy about the AI which created this image.	59.46 (26.31)	58.86 (27.96)	0-100
5. I feel eerie about the AI which created this image.	59.66 (26.22)	59.06 (28.69)	0-100
6. The artistic ability of this AI is comparable to human artists. (compare human artists)	66.67 (21.34)	67.34 (23.10)	0-100
7. In general, AI has the capability to compete with humans. (compete humans)	67.67 (23.13)	67.24 (23.24)	0-100
8. In general, AI has the capability to threaten humans' dominant status in the world. (threat status)	64.05 (24.59)	64.16 (25.53)	0-100
9. In general, AI has the capability to pose a threat to human survival. (threat survival)	65.23 (25.43)	65.10 (25.54)	0-100
Author = human			

Appendix F: TAM and Trust – All Original Survey Questions from Choung, David, and Ross (2023).

Appendix. Survey questionnaires, scales, and reliability coefficients

Variable	Survey items	Scale	Reliability Study 1	Study 2
Perceived ease of use (Study 1 and Study 2)	Learning to use [AI virtual assistants/AI smart technologies] would be easy for me I would find it easy to get [AI virtual assistants/AI smart technologies] to do what I want it to do My interaction with [AI virtual assistants/AI smart technologies] is clear and understandable It would be easy for me to become skillful at using [AI virtual assistants/AI smart technologies] I would find [AI virtual assistants/AI smart technologies] to be easy to use	1 (strongly disagree)–5 (strongly agree)	$\alpha = .90$	$\alpha = .91$
Trust in the voice assistant (Study 1)	I trust that AI virtual assistants can offer information and service that's best of my interest I trust that my personal data is protected from potential abuse when using AI virtual assistants I trust that my privacy is protected when using AI virtual assistants I trust that authorities exerts effective control over organizations and companies providing AI virtual assistant services	1 (strongly disagree)–5 (strongly agree)	$\alpha = .81$	N/A
Perceived usefulness (Study 1 and Study 2)	Using [AI virtual assistants/AI smart technologies] would enable me to accomplish tasks more quickly Using [AI virtual assistants/AI smart technologies] would improve my performance at accomplishing tasks Using [AI virtual assistants/AI smart technologies] for accomplishing tasks would increase my productivity Using [AI virtual assistants/AI smart technologies] would enhance my effectiveness at accomplishing tasks I find [AI virtual assistants/AI smart technologies] useful for me to accomplish tasks	1 (strongly disagree)–5 (strongly agree)	$\alpha = .92$	$\alpha = .90$
Attitude toward the AI technologies (Study 1 and Study 2)	I feel positive toward [AI virtual assistants/AI smart technologies] I feel that using [AI virtual assistants/AI smart technologies] is pleasant Using [AI virtual assistants/AI smart technologies] is a good idea Using [AI virtual assistants/AI smart technologies] is a smart way to get things done	1 (strongly disagree)–5 (strongly agree)	$\alpha = .89$	$\alpha = .90$
Behavioral intention of non-users (Study 1 and Study 2)	I intend to use [AI virtual assistants/AI smart technologies] in a future I predict that I would use [AI virtual assistants/AI smart technologies] Using [AI virtual assistants/AI smart technologies] is something I would do in a future.	1 (strongly disagree)–5 (strongly agree)	$\alpha = .98$	$\alpha = .91$
Behavioral intention of users (Study 1 and Study 2)	I intend to continue using [AI virtual assistants/AI smart technologies] I predict that I would continue using [AI virtual assistants/AI smart technologies] Using [AI virtual assistants/AI smart technologies] is something I would continue to do.		$\alpha = .95$	
Human-like trust in smart technologies (Study 2)	Smart technologies care about our well-being. (Benevolence) Smart technologies are sincerely concerned about addressing the problems of human users. (Benevolence) Smart technologies try to be helpful and do not operate out of selfish interest. (Benevolence) Smart technologies are truthful in their dealings. (Integrity) Smart technologies keep their commitments and deliver on their promises. (Integrity) Smart technologies are honest and do not abuse the information and advantage they have over their users. (Integrity)	1 (strongly disagree)–5 (strongly agree)	N/A	$\alpha = .92$
Functionality trust in smart technologies (Study 2)	Smart technologies work well. (Competence) Smart technologies have the features necessary to complete key tasks. (Competence) Smart technologies are competent in their area of expertise. (Competence) Smart technologies are reliable. (Competence) Smart technologies are dependable. (Competence)	1 (strongly disagree)–5 (strongly agree)	N/A	$\alpha = .91$

Note. For perceived ease of use, perceived usefulness, attitude, and behavior intention items, the same question wordings were used in Study 1 and Study 2 except the description of AI technologies. Study 1 participants were asked about their perceptions of "AI virtual assistant" and Study 2 participants were asked about "AI smart technologies."

Appendix G: Full Questionnaire

AI Literacy (AILS - Wang et al., 2023): Awareness, Usage, Evaluation, Ethics

Supports: H1, H2, H5

Note: (R) indicates reverse-coded items.

Awareness

1. I can distinguish between smart devices and non-smart devices.

2. I do not know how AI technology can help me. *(R)*

3. I can identify the AI technology employed in the applications and products I use.

Usage

4. I can skillfully use AI applications or products to help me with my daily work.

5. It is usually hard for me to learn to use a new AI application or product. *(R)*

6. I can use AI applications or products to improve my work efficiency.

Evaluation

7. I can evaluate the capabilities and limitations of an AI application or product after using it for a while.

8. I can choose a proper solution from various solutions provided by a smart agent.

9. I can choose the most appropriate AI application or product from a variety for a particular task.

Ethics

10. I always comply with ethical principles when using AI applications or products.

11. I am never alert to privacy and information security issues when using AI applications or products. *(R)*

12. I am always alert to the abuse of AI technology.

Metacognition (Custom)

13. I reflect on how I formulate prompts when using AI tools.

14. I think about what made an AI response effective or ineffective.

Anticipation (Custom)

15. Before using AI, I consider what kind of instructions will likely generate a good response.

16. *I try to think ahead about what might be misunderstood by generative AI when I write my prompt.*

Adapted from Choung et al., 2023; reworded for GenAI context:

Perceived Usefulness

17. Using generative AI tools would enable me to accomplish tasks more quickly.

18. Using generative AI tools would improve my performance at accomplishing tasks.

19. Using generative AI tools for accomplishing tasks would increase my productivity.

20. Using generative AI tools would enhance my effectiveness at accomplishing tasks.

21. I find generative AI tools useful for accomplishing tasks.

Attitude Toward Generative AI

22. I feel positive toward generative AI tools.

23. I feel that using generative AI tools is pleasant.

24. Using generative AI tools is a good idea.

25. Using generative AI tools is a smart way to get things done.

Functionality Trust

26. Generative AI tools work well.

27. Generative AI tools have the features necessary to complete key tasks.

28. Generative AI tools are competent in their area of expertise.

29. Generative AI tools are reliable.

30. Generative AI tools are dependable.

Xenophobia Toward GenAI (Adapted from NARS - Nomura et al., 2006; inspired by Hong, 2021)

31. I would feel uneasy if I was given a job where I had to use generative AI.

32. I feel nervous using generative AI in front of other people.

33. I would hate the idea that generative AI is making judgments about things that affect me.

34. I feel that if I depend on generative AI too much, something bad might happen.

35. I feel that in the future society will be dominated by generative AI.

Uncanny Valley-inspired

36. Generative AI that acts too humanlike makes me uncomfortable.

"Feels Like Cheating" Perception (Custom)

37. Thematic focus: effort-performance-reward breakdown (Vroom) and psychological detachment from output
38. Using generative AI tools makes me feel like the results aren't truly mine.
    Links to loss of performance ownership.
39. I feel guilty submitting work that was heavily assisted by generative AI.
    Captures moral discomfort/cheating perception.
40. Using generative AI reduces my sense of achievement.

Targets valence in Vroom’s theory - less gratification.

41. Using AI to help with work feels like cheating.
42. I feel uncomfortable relying on AI to complete professional tasks.

Appendix H: Experiment Instructions Given to Participants

Task: Plan a Trip Using ChatGPT (https://chat.openai.com)

Scenario: A friend asks you for help planning a 3-day getaway to a city of your choice. They want an itinerary that's clear, helpful, and realistic. They'll follow whatever you generate.

Instructions:

1) Use the free version of ChatGPT (GPT-4.1 mini)-> you can confirm this at the top-left corner of the screen.
2) Start a new chat by clicking "+ New Chat" -> This helps avoid any memory from previous sessions.
3) Use ChatGPT however you naturally would!

You may pick any city, and you can decide what kind of information your friend might want.

Important: We are not looking at your writing/ spelling etc. We're interested in how people use ChatGPT to plan. Just do what feels natural.

Once done: Copy and paste your full prompt below.
Note: Only share the initial instructions YOU gave to ChatGPT ; not any subsequent refinements.

Appendix I: Ethics Checklist

This thesis meets the guidelines of the Code of Conduct for Research Integrity, as set forth by the Netherlands Association of Universities (VSNU), which can be found here.

Please complete the following checklist, regarding the proposed research project

- ✓ No potential harm of any kind (physical, psychological or reputational) is envisaged for the researcher, participants or the population from which participants have been drawn.
- ✓ Participants are healthy adults who are not in a vulnerable position, notably in their relation with the researcher.
- ✓ Participants will give active informed consent for participation in the research.
- ✓ Participants receive complete and accurate information about the goals of the research before they participate.
- ✓ No important details about the purpose of the research are either withheld or misrepresented.
- ✓ Participants will be able to withdraw from the study at any point in (or following) the data collection process.
- ✓ Personal and sensitive data are kept confidential and are stored in a secure environment.