Department of Business Administration
FEKH38
Examensarbete i Business and Data Analytics
HT25

Age Differences in AI Usage and Confidence

How does AI usage among professionals differ across age groups, and do age differences affect confidence in AI-generated outputs?

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Sammanfattning:

Examensarbetets titel: Åldersskillnader i användning av AI och självförtroende.
Seminariedatum: 15 januari 2026
Ämne/kurs: FEKH38, Examensarbete i Business and Data Analytics, 15 ECTS
Författare: Axel Zetterman, Emanuel Evers, William Pagel
Handledare: Magnus Johansson
Nyckelord: Artificiell intelligens (AI), Organisationer, Åldersskillnader, Förtroende, Dunning-Kruger-effekten.
Forskningsfråga: Hur skiljer sig AI-användningen bland yrkesverksamma mellan olika åldersgrupper, och påverkar åldersskillnader förtroendet för AI-genererade resultat?
Syfte: Syftet med denna studie är att ge en bättre förståelse för åldersrelaterade skillnader i yrkesverksammas användning av AI och deras förtroende för AI-genererade resultat.
Metod: En kvantitativ fallstudie av skillnader i AI-användning bland yrkesverksamma baserat på ålder. Totalt genererade enkäten 95 användbara svar.
Teoretiska perspektiv: Studien utgår från *Theory of Planned Behavior & the Effect of Age on Usage* av Icek och Ajzen (1991) samt artikeln av Xu et al. (2024), "*New contexts, old heuristics: How young people in India and the US trust online content in the age of generative AI." Proceedings of the ACM on Human-Computer Interaction*. Vidare beaktas Dunning-Kruger-effekten såsom den beskrivs av Dunning och Kruger (1999)
Resultat: Inom enkät urvalet identifierades inget samband mellan ålder och användning av AI för professionella ändamål. Yngre yrkesverksamma rapporterade dock en större rädsla för att bli dömda av chefer och kollegor samt uttryckte ett högre förtroende för AI än sina äldre motsvarigheter. Bland respondenter med viss AI-kunskap uppvisade yngre deltagare högre genomsnittliga nivåer av självförtroende än äldre deltagare.
Slutsats: Studien undersökte åldersrelaterade skillnader i yrkesverksammas användning av AI och deras förtroende för AI. Inget samband identifierades mellan ålder och AI-användning i arbetet, vilket sannolikt kan förklaras av att respondenterna kom från organisationer som i hög grad betonar AI-användning och medarbetarutbildning. Yngre yrkesverksamma rapporterade dock ett högre förtroende för AI-genererade resultat än äldre kollegor, samt uttryckte en starkare rädsla för att bli dömda för att använda AI i arbetet. Vidare observerades högre nivåer av självförtroende bland yngre yrkesverksamma med viss förståelse för AI jämfört med äldre yrkesverksamma med samma nivå av AI-kunnande.

Abstract:

Title: Age Differences in AI Usage and Confidence
Seminar date: 15 January 2026
Course: FEKH38, Degree Project, Undergraduate level, Business Administration, Undergraduate level, 15 ECTS
Authors: Axel Zetterman, Emanuel Evers, William Pagel
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Keywords: Artificial intelligence (AI), Organizations, Age differences, Confidence, Dunning-Kruger effect.
Research question: How does AI usage among professionals differ across age groups, and do age differences affect confidence in AI-generated outputs?
Purpose: The purpose of this study is to provide a better understanding of age-related differences in professionals' AI usage and confidence in AI-generated outputs.
Methodology: A quantitative study of professionals' differences in AI use based on age. In total, the questionnaire yielded 95 usable responses.
Theoretical perspectives: The study draws on the *Theory of Planned Behavior & the Effect of Age on Usage* by Icek and Ajzen (1991) and the *Xu et al. (2024) article, "New contexts, old heuristics: How young people in India and the US trust online content in the age of generative AI." Proceedings of the ACM on Human-Computer Interaction*. The *Dunning-Kruger effect* as described by Dunning and Kruger in 1999.
Result: Within the survey sample, no relationship was identified between age and the use of AI for professional purposes. However, younger professionals reported a greater fear of judgment from managers and peers and expressed higher confidence in AI than their older counterparts. Among respondents with some AI knowledge, younger participants displayed substantially higher average confidence levels than older participants.
Conclusions: The study explored age-related differences in professionals' AI use and confidence. No association was found between age and AI use at work, likely because respondents came from organizations that strongly emphasize AI adoption and employee training. However, younger professionals reported greater confidence in AI outputs than older peers, and expressed a stronger fear of being judged for using AI at work. Furthermore, higher confidence levels were observed among younger professionals with some understanding of AI than among older professionals with the same level of AI literacy.

Preface:

This thesis would not have been possible without the support of several key contributors, whom we would like to acknowledge and thank. We would like to express our gratitude to our advisor, Magnus Johansson, for his support throughout the writing process. We would also like to thank Jacob Bergman for his assistance with code development and recommendation of the statistical approach. Finally, we extend our thanks to everyone who participated in the survey, as well as to the three pilot study participants, for their time and insightful feedback.

11 January 2026,
Axel, Emanuel & William

Glossary:

AI - Refers to outputs by data-driven methods that mimic aspects of human ability, such as information processing and intelligence as defined by Schintler & McNeely (2022). Hence, in this thesis, AI refers broadly to all types of artificial intelligence used across platforms and applications.

Confidence - “A feeling of having little doubt about yourself and your abilities, or a feeling of trust in someone or something” (Cambridge Dictionary, 2019)

Dunning-Kruger effect - Individuals with lower levels of knowledge tend to self-assess their actual knowledge less accurately than those with relatively higher levels of knowledge (Adamecz et al., 2025).

Usage - The use of something, which, within this thesis it mostly refers to the utilization of AI, both professionally and personally. (Cambridge Dictionary, 2022)

Professional - In this thesis, is defined as an individual who is actively working.

Effect of Age on Usage (EAU) - model created by Morris and Venkatesh (2000)

Theory of Planned Behavior (TPB) - Designed by Icek Ajzen (1991) to explain the different components that lead to human behavior.

Attitude towards using (ATU) - Refers to the end user’s own assessment of the perceived benefits and costs associated with adopting and using the new technology. (Morris and Venkatesh, 2000)

Subjective Norm (SN) - Refers to the peer and managerial influence. (Morris and Venkatesh, 2000)

Perceived behavioural control (PBC) - Refers to the level of ease or difficulty for using the technology. (Morris and Venkatesh, 2000)

1. Introduction and Research Problem

1.1 Introduction

Major technological advancements have always driven organisations to adapt and incorporate new innovations. Münter (2026) defines disruptive innovations as new technologies that enable significant improvements over existing technologies. Examples include the introduction of computers in the 1960s, the adoption of enterprise systems in the 1990s, and the emergence of the internet. One of the latest disruptive innovations is arguably artificial intelligence (AI). Even though the concept of AI was first introduced in 1956, recent advancements in computing power have sparked major interest in the field. AI is now widely expected to transform society by enhancing the cognitive capabilities of machines (Gressel et al., 2021). The AI boom accelerated with the launch of ChatGPT in late 2022, which marked a turning point in AI's capacity and accessibility (Bridgeman et al., 2024).

Research by Davenport and Ronanki (2018) found that 75% of executives familiar with their companies' use of cognitive technology believed AI would transform their businesses within 3 years. In parallel, Davenport and Ronanki describe how AI represents a fundamental shift in the way organisations interact with information, knowledge, and decision-making. Unlike previous technological advancements, AI, combined with deep learning, can analyse vast amounts of data across multiple layers, enabling it to produce human-like analysis and pattern recognition. Five years after their study, it seems like the executives who believed AI would transform industries were right. Workday (2023) conducted a survey in which 1,000 business decision-makers participated. Workday found that >90% of professionals reported using AI in their operations for tasks such as managing people and finances. Moreover, 80% of respondents said that AI and machine learning (ML) improved employee efficiency. In parallel, 80% agreed that AI and ML were required to maintain a competitive advantage in their business.

However, AI becoming more common within organisations may create issues. Hutzschenreuter and Lämmermann (2024) state that individuals often lack a proper understanding of the complex algorithmic behavior AI possesses. This can lead to incorrect outputs being accepted as correct, misuse of systems, or bias towards gender and race. Furthermore, the lack of understanding can lead to mistrust of AI. Hence, AI creates new opportunities but also poses certain risks.

As stated, individuals often struggle to understand the complex process of AI's algorithmic output. Consequently, this creates a "black box" in which some end users don't understand how AI reaches its conclusions while simultaneously lacking the tools or knowledge to verify AI output. As a consequence, firms that use AI could base decisions on incorrect outputs (Hutzschenreuter & Lämmermann, 2024). Moreover, Xu et al. (2024) found that generational differences in AI adoption and attitudes exist. Younger individuals used generative AI more extensively, adopted it more quickly, and generally viewed AI as the next tool for their online practices. A similar trend can be observed in Sweden (Internetstiftelsen, 2024). Among adults aged 18-34, 60% reported having used AI in the past year. This share declines to 34% among individuals aged 35-49, 26% among those aged 50-64, and only 10% among adults aged 65-84. These statistics highlight a substantial generational difference, with age negatively affecting AI usage. A cause could be younger generations' early exposure to AI, which makes them familiar with it. Skolverket (2024) states that 40% of students in upper secondary school were permitted by their teachers to use AI.

While younger generations tend to use AI more frequently, the retirement age for professionals is increasing (SCB, 2024). The share of individuals working beyond the age of 65 has risen from 10% in 2001 to 20% in 2023. At the same time, Grotti et al. (2018) show that certain industries have an uneven distribution of younger workers. As younger generations enter the workforce and older generations remain employed for longer, organizations increasingly face the challenge of navigating differences in AI usage across age groups.

1.2 Research problem

Given the introduction, questions arise about whether there is a difference in AI usage among professionals across different age groups. Furthermore, this thesis seeks to investigate whether age influences confidence in work-specific AI output. Specifically, this thesis examines whether younger professionals tend to exhibit overconfidence in AI results and, consequently, whether older professionals exhibit underconfidence.

AI systems are seldom transparent to the end users. Even when AI models present step-by-step reasoning in text, the underlying code and algorithms remain undisclosed, making it difficult for users to understand how outputs are generated or to judge their correctness. Overconfidence in AI can therefore lead to decisions based on unvalidated or incorrect outputs. Moreover, AI's algorithmic nature obscures the source and ownership of information, reducing traceability and complicating accountability when harm occurs, contributing to the accountability gap (Dignum, 2025). Dignum notes that end users typically lack insight into how AI decisions are made; explanations often describe the process at a high level but do not justify the normative validity of decisions. Bullock (2023) further argues that this problem is amplified when AI operates on complex data or in unregulated contexts with contested normative standards. In such cases, it is difficult to determine whether faulty AI-based decisions stem from biased data, code errors, or embedded value assumptions. Consequently, incorrect or harmful decisions may occur and remain unchallenged.

Real-world examples illustrate these consequences. The consulting firm Deloitte was required to partially refund the Australian government after delivering a report that contained multiple errors attributed to AI (Business Insider, 2025). Furthermore, Amazon faced backlash when an algorithm used for hiring penalised women, leading to discrimination in the recruitment process and bad publicity towards the company (BBC, 2021).

These examples indicate how a lack of accountability and insufficient understanding of algorithmic decision-making can lead to severe consequences. When users of the system don't understand the justification for the output, an accountability gap exists.

Concerns arise as AI continues to assist or even replace human decision-makers while evolving faster than individuals can update their skills (Guan et al., 2024). Guan et al. argue that "lags" in individuals' AI competence indicate that people may overestimate their abilities. Trust and confidence, therefore, play a significant role in how users respond to AI-generated recommendations. Horwitz & Kahn's (2024) findings show that individuals with more positive attitudes towards AI tend to place greater trust in the technology overall, making them more likely to follow the recommendations.

Moreover, Xu et al. (2024) found that young adults aged 18-24 perceive AI as a "supercharged" version of familiar technological tools such as search engines. Meaning, the trust they place in AI outputs is heuristic in nature and carried over from their prior experiences with traditional search engines. When the heuristic trust patterns shaped by previous experiences were applied to AI, they concluded that this led to overconfidence in both the AI's output and the individuals themselves. This confidence is further enhanced when AI usage is combined with time pressure or demands of efficiency. Furthermore, respondents with lower self-confidence in their ability to complete tasks were more likely to change answers when the AI suggested a correction. In parallel, EY (2024) warns that businesses and universities should avoid assuming that individuals born between 1995 and 2012 are "AI natives," as their findings indicate that, despite using AI most frequently, this group performs the poorest in critically assessing and identifying shortcomings.

The uncritical relationship can be explained as Automation bias, the tendency to place excessive trust in automated recommendations (Romeo & Conti, 2025). Such overreliance contributes to the perception of AI as a black box and the associated accountability gap, which seems more prominent among younger individuals.

Despite AI's shortcomings, research highlights numerous benefits for organisations and professionals who adopt it. For example, Rodriguez et al. (2025) found that, within B2B sales processes, AI implementation led to improved workflows, greater administrative efficiency, and increased sales. Similarly, Ma et al. (2024) showed that work-related use of AI positively affected boundary spanning and employee agility, enabling professionals to perform tasks beyond their core roles while performing more efficiently. Simultaneously, older employees tend to adopt technological tools more slowly than their younger counterparts (Fazi et al., 2025). Lower adoption and usage rates among older generations may therefore reduce organisational efficiency and competitive advantages. Furthermore, Deloitte's (2025) workforce index shows that trust in AI has decreased as the technology began to take over decision-making; similar results have been reported by Forbes (2025). The implementation of AI expansions is often seen as a threat, hindering effective AI adoption and use.

Age-related differences in AI usage and confidence can ultimately introduce noise and bias into organizational decision-making. Both these disparities produce predictable distortions (bias) and random variations (noise), consistent with Kahneman et al.'s (2016) distinction between the two types of errors in human decision-making. When such tendencies coexist within the same workplace, undesirable decisions may arise, not because of differences in organizational information, but because of variations in users' AI competence and confidence. Rather than standardising decision processes, AI can therefore contribute to discrepancies. In summary, if older employees underuse AI, organisations may miss out on efficiency gains and competitive advantages, while younger employees' overconfidence can lead to automation errors.

1.3 Research question

How does AI usage among professionals differ across age groups, and do age differences affect confidence in AI-generated outputs?

2. Theoretical perspective

The theories discussed in this chapter provide a framework for understanding how age differences influence professionals' AI usage and confidence in AI-generated output. Morris and Venkatesh's (2000) rework of Icek Ajzen's (1991) Theory of Planned Behavior, together with additional research on the effects of age on technology adoption, further illuminates the relationship between professionals' age and their technology use. This foundation helps clarify why certain age groups may readily embrace AI while others remain more hesitant.

At the core of these behavioural differences lies one of the foundations of human decision-making: bounded rationality. Bounded rationality limits the decision-making process to the information available to individuals and to human capabilities constrained by cognitive and situational limitations (Simon, 1957). Situations in which one is forced to make purely rational decisions are often constrained by insufficient information or limited resources. This leads to decisions being made through simplified processes, guided by intuition and heuristic trust patterns (Miller et al., 2002). In relation to AI usage and confidence, this helps explain why users may rely on AI-generated output to make quick decisions, often without validating its accuracy.

The behavioural differences and confidence placed in AI-generated output can also be contextualised through the Dunning-Kruger effect (Dunning and Kruger, 1999), which describes how individuals with limited subject-matter expertise tend to overestimate their abilities. By comparing these theoretical perspectives with empirical observations, we aim to provide the reader with a comprehensive understanding of the concepts examined in this paper and a deeper insight into generational dynamics in AI usage and confidence.

2.1 Theory of Planned Behavior & Effect of Age on Usage

Icek Ajzen (1991) presents the *Theory of Planned Behavior* (TPB), which explains the components that lead to human behavior. According to the model, three factors determine human behaviour: Attitude toward the behaviour, Subjective norm, and Perceived behavioural control. Which ultimately determines the extent to which a person intends to perform or refrain from performing the behavior. When discussing the three mentioned factors, they are interpreted as follows. *Attitude toward the behavior* refers to an individual's understanding of the consequences of performing the behavior. *Subjective norm* refers to the social pressure to perform or not to perform the behaviour. Lastly, *Perceived Behavioural Control* relates to the individual's ability to actively choose to perform or not perform the behaviour.

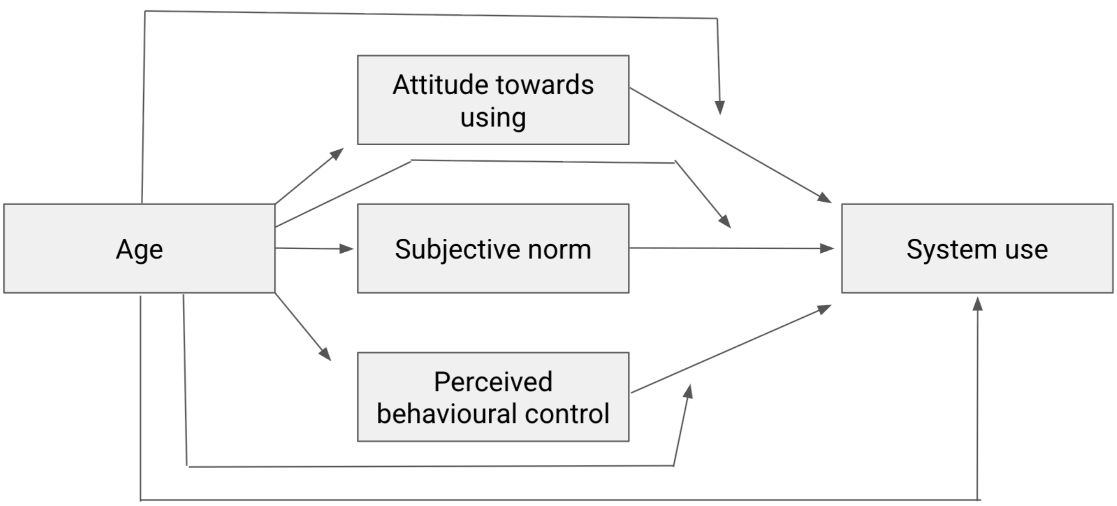
Morris and Venkatesh (2000) further developed TPB by incorporating age into their model, *Effect of Age on Usage* (EAU). They conducted a study over a five-month period that investigated the drivers of new technology adoption and the degree of usage among professionals of different ages within organisations. The definitions of the variables leading up to the system use, described as behaviour in TPB, were slightly altered to place them in a technology-use context. The biggest change to the model was that EAU removes intention as a leading variable for performing or not performing a behaviour. Moreover, within the EAU, the component Attitude towards using (ATU) now refers to the end user's assessment of the perceived benefits and costs of adopting and using the new technology. As a fictive example, one individual might view the behavior of using AI as leading to an improved efficiency of everyday monotonous tasks, or they might feel the need to know how to leverage AI usage in order to remain competitive in today's job market, which was described as the case for young adults by Xu et al. (2024). Another person, however, might perceive the same behavior as negatively affecting their output quality if they do not understand the results produced by AI and therefore refrain from using it.

Subjective Norm (SN) refers to the peer and managerial influence (Morris and Venkatesh, 2000). As a hypothetical example, if all peers within an organisational department use AI to automate a specific task, it may pressure individuals who continue to perform the task manually to adopt AI, since AI is the norm within the organisation. Or, conversely, early AI adopters within an organisation might fear being viewed as inattentive, since they outsource tasks they should be able to solve independently.

Perceived behavioural control (PBC) is further described as the level of ease or difficulty in using the technology (Morris and Venkatesh, 2000). For example, some professionals who mainly perform manual, repetitive tasks might see a clear use case for AI to mimic their work. In parallel, professionals whose work is primarily non-repetitive may find it difficult to implement AI to improve efficiency. Another interpretation could concern how difficult professionals perceive AI usage to be, particularly if they lack prior experience.

Morris and Venkatesh (2000) state that all three factors mentioned are directly affected by the age of the system user. The assumptions of EAU are:

1. Age has a direct effect on system usage
2. Age has an effect on ATU, SN, and PBC
3. Age has a direct influence on the ATU - System Use, SN - System Use, and PBC - System Use relationships
4. Age has no significant direct effect on system usage over and above the effects of ATU, SN, and PBC



Graph 1: recreation of the model EAU by Morris and Venkatesh (2000)

Morris and Venkatesh (2000) concluded that younger professionals were notably more affected by ATU when using a new technology than their older peers. In parallel, older professionals were more affected by SN when deciding the level of usage. The conclusion was that younger professionals appeared to be driven to a high degree by attitudinal factors, whereas older professionals were driven by social and process factors. Moreover, PBC was positively associated with age, but to a lesser degree than SN.

Morris and Venkatesh (2000) further discuss why attitudinal factors play a more significant role among younger workers. They argue that younger individuals have been exposed to information technology from a relatively early age, in some cases as early as elementary school. In contrast, personal computers were far less accessible when older professionals were in school or university, particularly prior to the 1990s. As a result, older professionals had fewer opportunities to engage with and recognize the benefits of information technology early in life and were therefore more influenced by other factors. A similar argument can be made about younger professionals and AI.

As previously stated, Skolverket (2024) highlights that 40% of Swedish students were allowed to use AI in upper secondary school. The introduction of AI in schools is interesting in light of Tijdens and Steijn's (2005) research, which investigated the components that affect individuals' mastery of Information and Communication Technology (ICT). 32% of respondents under 30 said their school played an important role in their journey to mastering their most frequently used ICT; the rate among older respondents was significantly lower. Moreover, Koning and Gelderblom (2006) report that younger professionals use ICTs more frequently than their older peers. One explanation is that older workers generally find it more challenging to process large amounts of information in a short period of time. Morris and Venkatesh's finding that young professionals use newly implemented technologies more aligns with Mayer’s (2009) finding that professionals over 30 are less likely to adopt new technologies. Moreover, the probability of non-adoption increased progressively with age.

In light of the theory EAU as presented by Morris and Venkatesh (2000), this thesis examines how age influences professionals’ use of AI, and moreover, how age affects the three sub-categories, SN, ATU, and PBC, that ultimately decide the level of usage.

2.2 Dunning-Kruger

Dunning and Kruger (1999) present in their article *Unskilled and Unaware of It: How Difficulties in Recognizing One's Own Incompetence Lead to Inflated Self-Assessments* that people tend to hold overly positive beliefs about their own abilities when they lack the necessary knowledge or skills to accurately assess their performance. This theory was tested as the authors conducted four empirical studies in which the participants completed objective tasks in different domains: humor, logical reasoning, and grammar, and were then asked to estimate both their absolute performance (for example, number of correct answers) and their own relative standing compared to peers. By comparing these self-evaluations with actual test results, Dunning and Kruger demonstrated that participants in the bottom performance quartile consistently and dramatically overestimated their abilities, whereas high performers showed more accurate and even modest self-assessments.

The reasoning was further developed by Dunning and Sanchez (2018), who demonstrated that individuals with minimal experience often begin with a relatively accurate sense of their own ability. At an early stage, people tend to be self-aware enough to recognize that they are beginners and therefore consequently, do not possess inflated confidence. This suggests that people do not begin in a Dunning-Kruger state; rather, as they gain a small amount of experience, they form quick, oversimplified theories about the task, which produces what the authors refer to as a “beginner’s bubble”. The bubble refers to a temporary spike in unjustified confidence that rises much faster than actual skill. This overconfidence diminishes through feedback and continued learning. Consequently, performance and self-assessment begin to realign more accurately over time.

These dynamics were further captured in AI use through a study by Horowitz and Kahn (2024). The authors' aim in the study was to examine how AI adoption across vital societal functions would be implemented. The findings showed that those with the least experience in AI tend to show mild algorithm aversion, meaning a slight caution towards AI, but as individuals gain a bit more knowledge, automation bias begins to emerge, peaking at lower levels of knowledge.

The pattern and the role of confidence during the early stages of an individual's learning are interesting while researching how people interact with AI. Further developing on the idea of the “beginner’s bubble”, Guan et al. (2024) showed that people who have just started learning about AI often fall into a similar trap: they overestimate their ability to understand and critically assess AI systems, leading to cognitive bias. Their study, executed by 150 MBA students, was divided into 4 quartiles based on the actual AI knowledge. The ones that had the least amount of AI knowledge were placed in the 1st quartile, and the most in the 4th quartile. The result showed that participants who had just started learning (1st quartile) and had superficial knowledge (2nd quartile) of AI had the highest perceived self-efficacy relative to their actual AI knowledge, indicating a lack of the in-depth understanding required to evaluate potential risks or limitations. In contrast, the 3rd and 4th quartiles demonstrated a more stable and accurate sense of confidence in their knowledge, often showing greater caution and resilience.

However, the latest research on Dunning-Kruger presents a contrasting pattern to earlier studies. Fernandes et al. (2026) show that AI users achieved higher scores, but systematically overestimated their own predicted performance. The results further showed that the ones with the highest level of AI literacy were the most overconfident. Rather than showing the typical overconfidence predicted by the Dunning-Kruger effect, increased AI-related knowledge was associated with greater confidence inflation, unrelated to their actual ability. Indicating a reshape in the classic Dunning-Kruger path.

2.3 Formulation of hypotheses

2.3.1 Age is negatively interrelated to the use of AI tools

Morris and Venkatesh's (2000) model EAU assumes that age affects system usage. Assuming AI shares the same barriers and drivers to usage as other technological tools implemented in the workplace, younger professionals are expected to exhibit a higher degree of AI usage than their older peers. This expectation is further supported by findings from EY (2024), which presented that a majority of individuals aged 17-27 used AI. In parallel, Babu et al. (2024) found that being born between 1995-2012 alone positively influenced whether an individual used the AI system ChatGPT. Moreover, Xu et al. (2024) report that younger individuals use AI to a greater extent than their predecessors. Younger individuals were more inclined to use AI because they viewed it as a natural extension of their existing online habits. Building on Koning and Gelderblom’s (2006) argument that older professionals use ICTs less frequently because they find it more difficult to process new information rapidly, this thesis assumes that a similar explanation may apply to the age differences observed in other studies on AI usage.

To gain an overview of how AI is used in organisations today, interviews conducted by Aramali et al. (2025) provide direct insight into professionals’ perspectives on AI across different age groups. Respondents expressed that younger individuals tend to embrace AI more readily, while older colleagues often lag in adoption. Moreover, one respondent noted generational differences in attitudes toward integrating AI at work, suggesting that older professionals may be more resistant to change, whereas younger staff are already far more accustomed to AI technologies. Moreover, KPMG, together with the University of Melbourne (2025) provides insight into how AI is currently being used by professionals across different age groups. The study distributed surveys to 48,340 respondents originating from 47 countries. When grouping professionals into three age categories: 18-34, 35-54, and 55+, a notable pattern emerged. More than two-thirds of respondents aged 18-34 reported using AI at work, compared with only 40% of those aged 55 and above. The decrease in usage with increasing age is further supported by Mayer's (2009) findings, which showed that the probability of ICT system adoption amongst professionals declines once their age exceeds 30.

Hence, we hypothesize:

H1: Age is negatively interrelated to the professionals' use of AI tools

2.3.2 Previous exposure to AI affects younger professionals' AI usage in their line of work

Morris and Venkatesh (2000) offer another plausible explanation for why younger professionals were more inclined to adopt new technologies. The hypothesis is that because younger individuals have been exposed to technology earlier in life, perhaps since attending school, they are consequently more likely to accept and adopt new technological advancements as professionals. Furthermore, younger individuals' overall exposure to technology was far greater than that of their older peers. The same assumptions seem applicable to AI usage as well. Stöhr et al. (2024) conducted a survey study across Swedish universities, with 5894 students as respondents. The results showed that 44.2% of students were familiar with and regularly used AI within their academic work. Hence, young individuals' experience with AI during their academic studies may have a spillover effect once they enter the job market, making them more likely to use AI in their professional roles.

The claim by Shao et al. (2024) that top-performing students are often the drivers of progress and change within organisations aligns with EY's (2024) study. This claims that Gen Z will be a key driver of AI adoption, as they are expected to make up 30% of the global workforce by 2030. This suggests that the growing presence of Gen Z in the workforce will significantly influence organisational AI adoption and, in parallel, its use.

H1a: Previous exposure to AI affects younger professionals' AI usage in their line of work

2.3.3 - The effect of Age on ATU

Furthermore, EAU assumes that age influences the three subcategories: ATU, SN, and PBC, which all ultimately affect the level of technology usage. Staying consistent with the findings of Morris and Venkatesh (2000), who showed that younger professionals were influenced to a higher degree by ATU, we hypothesize:

H1b: The belief that the benefits of AI usage outweigh its costs is interrelated with age.

H1c: Agreement of necessity to use AI tools in order to keep up with the workload is interrelated with age

H1d: Agreement that using AI increases the likelihood of incorrect or misleading information is interrelated with age

H1e: Agreement of necessity to use AI in order to stay relevant in today's job market is interrelated with age

2.3.4 - The effect of Age on SN

In contrast, older professionals' usage of newly implemented technology showed a higher tendency to be affected by SN Morris and Venkatesh (2000). Hence, we further hypothesize:

H1f: The degree of influence peers or managers have over professionals' use of AI is interrelated with age

H1g: Age is interrelated with higher perceived judgment from peers or managers regarding the use of AI.

2.3.5 - The effect of Age on PBC

Morris and Venkatesh (2000) further show that age should positively affect the subcategory PBC. Their argument is that older professionals have weaker cognitive abilities than their younger peers. This is once again supported by the claim made by Koning and Gelderblom (2006) that older professionals have a harder time processing large amounts of information in a short period of time. Hence, help guides on how to use the system would be more appreciated by older professionals. Morris and Venkatesh's (2000) findings show that PBC and age were positively interlinked. Thus, we hypothesize:

H1h: Perceived ease of use of AI amongst professionals is interrelated to age.

2.3.6 - Age is negatively interrelated to confidence in work-specific AI-generated outputs

Miller et al. (2002) state that decisions are made through intuition and heuristic trust patterns. One of these heuristics is confidence. Research shows that individuals use confidence as a heuristic cue to evaluate the reliability of information when operating under conditions of uncertainty (Thomas & McFadyen, 1995). The confidence heuristic describes how people assess the informational quality of arguments based on how confidently they are expressed rather than on their substantive content. These scenarios are most common in contexts where both individuals share a common interest and want to exchange information efficiently. While Thomas and McFadyen's (1995) paper was demonstrated in a human-to-human context, research indicates that individuals often apply the same social heuristics when engaging with technological systems. For example, studies in human-machine interaction show that users project social qualities to computers and respond to cognitive shortcuts (Von der Pütten, 2010).

Chong (2022) further demonstrated that confidence in an AI system's ability to perform a given task is secondary to individuals' self-confidence. Specifically, participants' preparedness to trust the executor played a more decisive role than trust in the AI itself when determining whether they accepted or rejected AI-generated outputs.

The finding shows that users rely less on their belief in AI's competence and more on their own ability to evaluate and use the AI's output. When AI systems produce outputs that align with users' expectations, perceived successful interaction can reinforce self-confidence. This mechanism is similar to Thomas & Macfadyen's (1995) study, as it is quick and efficient, while exchanging common interests to solve the problem presented to the end user. Such confirmation may increase perceived AI reliability while strengthening users' own confidence in their evaluative ability. When viewed through the lens of the Dunning-Kruger effect, this can explain the early spike in self-confidence that arises when individuals possess limited knowledge. Users at this stage may assume they can tell when the system is right or wrong, even though they lack the necessary competence. Furthermore, Dunning and Sanchez (2018) found that beginners in a subject often have an accurate sense of their own ability. However, as they reach a level of competence just above beginner level, overconfidence tends to occur, creating a 'beginner's bubble, where internal judgment is likely to dominate an informed assessment. This works in line with Xu et al. (2024) who found that the use of AI and overconfidence among 18-24 year olds emerge in environments characterised by time pressure, demands for efficiency, and the quest for comfort. Under such conditions, individuals rely on heuristics shaped by prior experience with technology rather than evaluating the reliability of AI outputs, as suggested by Millers et al.'s (2002) work on bounded rationality.

Kahneman & Klein (2009) further argue that extensive professional experience is necessary for the development of skilled intuition, as intuition develops through exposure to valid cues and consistent, positive feedback. This type of expertise is not immediately acquired but develops through practice and experience in decision-making. On this basis, we assume that tendencies toward critical evaluation skills and a more accurate sense of self-assessment are more likely to emerge later in work, as experience builds understanding of the tasks performed and establishes heuristic trust patterns. In a scenario where AI presents its output, we assume that older professionals can critically assess it and, consequently, support or reject it. In parallel, we therefore assume that younger professionals exhibit greater confidence, since they are assumed to lack the equivalent abilities and skills to validate or reject AI output.

In order to be able the test theoretical perspectives against respondents in regards to their knowledge, the following hypotheses have been formulated;

H2: *Age is negatively interrelated to confidence in work-specific AI-generated output*

H2a: *Younger individuals exhibit higher perceived levels of skills and knowledge related to using AI to enhance efficiency.*

H2b: *Younger individuals rely more on AI to support decision-making in their line of work*

H2c: *Younger individuals report higher perceived understanding of how AI systems, algorithms, and data models function*

2.3.7 - Individuals with some AI knowledge, confidence in work-specific AI-generated output decreases with age.

Following the reasoning of Dunning and Kruger (1999) and the findings of Guan et al. (2024), who observed that novices in the field of AI often fall into the same cognitive trap, builds the hypothesis theoretical foundation. Age has received limited attention as a primary explanatory variable in prior research on AI usage and the Dunning-Kruger effect. As younger generations enter the workforce, this thesis considers age-related differences in confidence in AI-generated outputs to be of significant interest. The relationship between age and confidence described in H2 assumes that older professionals have less confidence in AI output because of their existing intuitions and trust patterns. Building on that point, Kahneman & Klein (2009) further argue that experienced professionals and experts are more likely to be aware of the cues that guide them and to recognize when they don't know, compared to non-experts and/or individuals whose intuitions are not skilled. We therefore expect that, among individuals with some AI knowledge, confidence in AI-generated outputs will decrease with age.

Thus, this thesis further hypothesises:

H3: *Confidence in work-specific AI-generated outputs among individuals with some AI knowledge decreases with age*.

3. Methodology

3.1 Research design

This thesis used a quantitative approach. By collecting survey data, we used a deductive approach to compare it with the theories to test our hypothesis. The approach of using a quantitative research model in order to deductively and inductively test a theory is in accordance with Bell, Brym, and Harley in Business Research Methods (2019)

When developing the hypotheses H1 & H2, sub-hypotheses were used to refine and test their significance. By employing sub-hypotheses, the underlying theories can be decomposed, enabling a more detailed examination of the main hypothesis and a deeper investigation of the proposed relationships. If the main hypothesis were supported, the sub-hypotheses could be used to further explore the reasons for its acceptance or, conversely, to examine why it might not be rejected in favor of the null hypothesis (Heger et al., 2021).

3.2 Sampling approach

Bell, Bryman, and Harley (2019) emphasize the importance of creating an appropriate research setting, which, in this thesis, meant limiting participant recruitment to individuals in the workforce. Accordingly, this thesis focuses on professionals currently in the workforce, aged 18 to 59. For analytical purposes, ages were grouped into the ranges 20-29, 30-39, 40-49, and 50-59. By categorizing age into fixed intervals, the different age groups could be compared on equal terms (Bell, Bryman, and Harley, 2019). The decision to limit the sample to individuals under 60 was based on difficulties recruiting older respondents who are still active in the workforce. To identify eligible participants, data collection was primarily conducted by recruiting respondents from three organisations across different industries, tobacco, dairy alternatives, and telecommunications, supplemented by respondents found on the street in Malmö. As a result, a substantial proportion of respondents were employed by one of these three organisations, with approximately 20% coming from outside them. The demographic profile of these organisations shows that employees aged 60 and over are underrepresented. Additionally, all three companies actively promote the use of AI, which is expected to contribute to more informed and balanced responses. However, this approach excludes professionals from sectors such as services, organisations that do not actively promote AI, and other workforce groups. Although some of these perspectives may be partially captured through respondents recruited outside the three organisations, the sample remains centred around the main organisations and should therefore be considered when interpreting the findings.

3.3 Data collection and questions

The data collection method selected was a survey distributed via Google Forms. The questionnaire design followed the methodological recommendations outlined by Bell, Bryman, and Harley (2019). The motivation for using a survey was to eliminate the potential risk of interviewer variability (Bell, Bryman, and Harley, 2019).

To ensure high response quality and ease of completion, the questionnaire was kept concise and divided into three clear sections. At the beginning of the form, respondents were informed that it would take no more than 7 minutes to complete. Providing this time estimate helps set expectations and reduces the likelihood that respondents disengage due to perceived time commitment. When creating the questions, careful consideration was taken to ensure the answers were not easy to dismiss. An example of this is our approach to testing AI literacy. The decision to include a self-evaluation of AI literacy prior to the knowledge test was based on the assumption that respondents who reported some knowledge of AI understanding would be less likely to skip the subsequent section assessing their actual AI literacy, as doing so could potentially disprove their self-stated level of knowledge. Additionally, all questions were initially made mandatory to ensure that no items were unintentionally overlooked. Unfortunately, when creating the final version of the survey distributed to respondents, the mandatory answer option was inadvertently removed, an issue only discovered after responses had been received, resulting in six answers being removed because they were not entirely filled in. Because incomplete responses were few, it was decided to exclude them entirely.

To improve the quality of our survey data, professionals within the selected organisation were consulted for feedback on the questions. Moreover, before sending out our survey, a pilot test was conducted with satisfactory results. Three people outside the organisations gave feedback on survey improvements as recommended by Bell, Bryman, and Harley (2019). This process allowed us to measure the time required to complete the survey, make final adjustments, and ensure that all questions were clear, easy to understand, and easy to answer.

This means that due to the complex nature of the underlying theories, our approach was to approximate the intended meaning of constructs such as SN as accurately as possible. The assumption was that directly asking respondents whether SN affected their professional AI usage would be ineffective, as such questions may be easily misunderstood. Instead, when examining the effect of SN on AI usage, it was deemed necessary to carefully design the survey questions to better understand whether SN influenced AI usage. Several more specific statements, such as "My use of AI for work tasks is influenced by my peers or managers," were therefore employed to provide deeper insight into how SN shaped professional behaviour and, in turn, led to the sub-hypothesis.

3.3.1 Structure of the Survey

The majority of the survey uses a Likert scale; each response category is assigned a predetermined numerical value from 1 to 5, allowing for efficient aggregation and comparison of results across respondents. Additionally, variation in item phrasing can help reduce the risk of response bias. For example, presenting both the statements "I am generally happy" and "I am generally very unsatisfied with my life" allows identification of inattentive response patterns, such as respondents consistently selecting the same extreme value without careful consideration (Bell, Bryman, and Harley, 2019).

The survey was divided into three sections, with the first aimed at establishing a demographic and experiential profile of the respondents, including age, AI knowledge, and prior AI use in both personal and professional contexts.

The second section of the survey included statements followed by five options indicating their level of agreement: Strongly agree (5), Agree (4), Undecided (3), Disagree (2), and Strongly disagree (1), inspired by (Bell, Bryman, and Harley, 2019). All questions in this section were closed-ended to ensure standardized responses and to facilitate quantitative analysis. The survey questions were designed to test hypotheses developed earlier in the thesis.

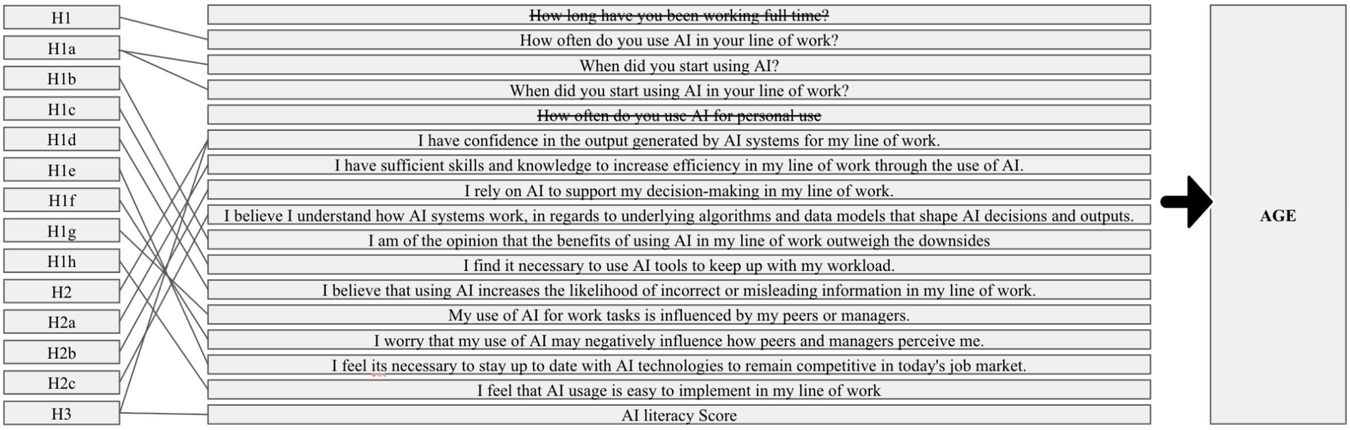


Figure 1: Connection between hypothesis and survey questions

Figure 1shows two crossed-out questions. These questions were included in the survey and later deemed irrelevant as the theoretical framework evolved. Consequently, responses to "*How often do you use AI for personal use?*" and "*How long have you been working full time?*" were excluded from the analysis. These questions were excluded because the age at which respondents began using AI was deemed a more relevant predictor of AI usage, and age was considered a more appropriate predictor than total years of employment. The last section, "*AI Literacy score,*" summarizes the knowledge score the respondent accumulated.

To make the Chapter 4.0 analysis more accessible to readers, the survey questions were grouped into categories, and the relationships among questions, categories, and hypotheses are shown in Table 1 in Appendix 7.4, Methodology. This approach was intended to provide a clearer understanding of the purpose behind each question and of what was tested in relation to the independent variable Age. The same line of reasoning has been applied when formulating the hypothesis.

The last part of the survey was an AI literacy test. The answers were ordinal and were scored based on total points accumulated. (Bell, Bryman, and Harley, 2019). This section was included to evaluate whether respondents' perceived understanding of AI corresponded with their demonstrated knowledge, thereby providing insights related to the Dunning-Kruger effect (Guan et al., 2024). The intention was to identify whether individuals who rated themselves as having a high level of AI understanding might, in fact, possess lower levels of actual knowledge, and conversely, whether respondents who rated their understanding as low might demonstrate higher than their self-perceived knowledge.

The knowledge-testing questions and corresponding point system were developed based on Guan et al.'s (2024) framework. In their study, a point system was used to determine participants' overall understanding of AI based on their responses. New questions were created in this thesis inspired by the framework, as shown in Table 2.

Furthermore, although personal AI usage was not included in the hypotheses, it was examined to assess whether it could provide additional insights. Accordingly, this aspect was analyzed using descriptive statistics in Table 5.6 and tested for statistical significance in Table 7, following the structure presented below.

Question	Category
How often do you use AI for personal use?	Private use of AI tools

Table 1.1: Personal use of AI categorisation

Questions	Answers					Points				
Which of the following terms best represent the technology that builds the core of a modern, intelligent AI system?	A	B	C	D	E	1	0	3	2	0
What are the purpose and objectives that AI is designed to achieve?	A	B	C	D	E	1	3	2	0	0
How can AI perform the tasks it was designed to do?	A	B	C	D	E	1	0	2	3	0
In how AI performs tasks, which part of the process is directly connected to autonomous learning? (Autonomous learning refers to an AI system's ability to independently acquire, refine, and adapt knowledge or behavior without requiring explicit human programming for each new task or condition)	A	B	C	D	E	1	0	2	3	0

Table 2: Points system for knowledge questions within the survey.

In Table 2, each AI-literacy question offered five options with varying levels of accuracy. Points were assigned based on how accurately each response addressed the question, determined by the number of correct terms used. The accumulated points provided an indication of respondents' AI knowledge and were subsequently divided into four AI-knowledge quartiles:

1st quartile - minimal understanding of how AI works: 0-3 points
2nd quartile - some understanding of how AI works: 4-6 points
3rd quartile - good understanding of how AI works: 7-9 points
4th quartile - strong understanding of how AI works: 10-12 points

3.3.2 Analysis of responses.

The first step in analyzing the collected data was to identify respondents who had skipped one or more questions. In total, six respondents (n = 103) had incomplete answers. Moreover, responses from participants aged 60 or older were excluded due to an insufficient sample size, as only 2 respondents were in this age group. Resulting in a final sample size of n = 95. The respondents' age intervals are visualized using a frequency table shown in Analysis Table 4, which presents the number of participants in each age category as a percentage distribution (Bell, Bryman & Harley, 2019).

The next step of the analysis was to ensure that all remaining responses were consistently converted into whole numbers without decimals, as recommended by Bryman and Bell (2017). Once it was confirmed that none of the respondents had used decimal values, all responses except age were transformed into numerical values using formulas in Google Sheets, where the conversion of text responses into numerical data was conducted in order to follow a Likert scale and enable quantitative analysis (Bell, Bryman, and Harley, 2019). This procedure is further illustrated in Appendix Table 8.

The analysis of responses was divided into two sections, with the first using Python to determine whether the hypotheses were statistically significant, and the second using contingency tables to further test the hypotheses.

3.3.2.1 Python code development

In accordance with Bryman and Bell (2017), we did not wait to develop our code until all respondent data had been collected. The most appropriate methods for testing the significance of our hypotheses were ordinal logistic regression. Moreover, Bryman and Bell (2017) highlight the importance of becoming familiar with the chosen platform before developing the code. Therefore, Python was selected, as all three authors had attended workshops on statistical modelling in Python.

During the survey construction and coding process, careful consideration was given to which survey questions were associated with each hypothesis and to how these connections were defined, to establish a clear coding scheme. Furthermore, a critical assessment of the code was conducted and further refined until the outcome was consistent across different approaches to ensure validity (Bryman and Bell, 2017).

3.3.2.2 Ordinal logit

To test our hypothesis, we used an ordinal logistic regression model. Inspired by code conducted by Riswanto (2025), the Python code outputted a p-value (probability value) that assessed whether a statistically significant relationship existed within our survey responses.

In general, Ordered Logit models are suitable when testing the interlinkages between an ordinal response variable, such as age, and one or more explanatory independent variables, such as respondent knowledge assessment or confidence in AI-generated output (Parry, 2016). Following Williams' (2020) explanation of Ordered Logit Models, the dependent variable was respondents' self-assessed confidence on a 1-5 Likert scale, while age and AI literacy score were independent variables. The equation used to test our hypothesis was calculated in Python and subsequently adjusted for the different hypotheses. For example, for H3, we combined Age and Knowledge quartiles into a single independent variable to test whether age, combined with actual knowledge, was associated with confidence.

The p-value output indicates the probability of observing the data under the assumption that no interlinkage exists. Each hypothesis is tested against a null hypothesis that assumes the absence of a relationship. A p-value greater than 0.05 suggests that the data are consistent with no interlinkage and therefore leads to rejection of the hypothesis in favor of the null hypothesis. Conversely, a p-value of 0.05 or lower indicates statistical significance, supporting the hypothesis and leading to rejection of the null hypothesis.

3.3.2.2.1 Critique against Ordinal Logit

The chosen statistical method, ordinal logit, is not without limitations. Williams (2016) argues that the proportional odds assumption must hold for ordinal logit models to yield accurate results. If there are variances between the proportion of answers respondents, for example, if 35% of respondents over the age of 30 select “I completely agree” while the remaining 65% choose one of the four other response options, the ordinal logit model would underestimate the impact of age on shifting respondents away from “I do not agree at all.” At the same time, it would overestimate the probability associated with age for the “I completely agree” category. Williams (2016) further notes that ordinal logit models are frequently used in studies but recommends other statistical models that better accommodate proportional variances.

3.3.2.2.2 Justification of Ordinal Logit

The choice to use an Ordinal Logit model was made because ordinal regression models provide a valid probability distribution for the possible outcomes, rather than a single point estimate, and allow uncertainty in the predictions to be explicitly represented. In addition to the model parameters being interpretable as the effect a single predictor has on the outcome, given that all other predictors are held constant. This provides deeper insight into the likelihood of the hypothesis being true, making the ordinal logit model a clear choice for this thesis. However, the more complex a model is, the harder it is to understand how a single factor affects the result, which has been taken into account when using the model (Kook et al., 2022).

3.3.2.3 Analysis through contingency tables

The second part of the analysis involved creating contingency tables. This was done to provide a clear overview of descriptive statistics between the different questions and age groups. It's worth noting that contingency tables can demonstrate relationships between variables, but do not prove causality. Instead, they provide an indication of plausible associations or explanations. (Bell, Bryman, and Harley, 2019).

Furthermore, the questions were divided into categories corresponding to the different hypotheses and theoretical perspectives, in order to provide a clear overview of how the questions were related, as shown in Appendix Chapter 8.3 Methodology, Table 3.

The category division shown in Table 3 was created to provide a clearer overview of how the questions relate to the different hypotheses and aspects of AI use that this thesis aims to explore. ATU evaluates participants' perceived benefits and costs towards AI usage. SN assesses participants' perceptions of the influence of coworkers and managers on their AI-use. The self-literacy score is based on the Dunning-Kruger effect and evaluates participants' confidence in their ability to use AI. The AI literacy score measures participants' knowledge of how AI works, and PBC describes whether participants believe AI is easy to implement and use.

The arithmetic mean for the self-literacy score, AI literacy score, and age category was calculated and presented in Table 6 (Bell, Bryman, and Harley, 2019) as a contingency table. The scores presented in Table 6 are based on the maximum and minimum possible scores within each category. The *AI literacy score* ranges from 0 to 12, where 12 indicates a strong understanding of how AI works. The *self-literacy score* ranges from 4 to 20, with 4 indicating very high confidence in one's ability to use AI.

To provide further insight into potential patterns, questions associated with the different hypotheses were compiled in Table 5. The table presents the percentage distribution of responses across age categories, illustrating variations among different age groups. To make these individual responses even clearer, some questions were categorized by age and displayed as combined bar charts, which clearly show the percentage distribution across the different response alternatives within each age group. These graphs are presented as complementary to Table 5, named Graph 5.1.1-5.6.1, located in Appendix 8.4 Analysis (Bell, Bryman and Harley, 2019).

The scores collected under the self-literacy test section were inverted, as a value of 5 corresponds to 'strongly disagree' and 1 to 'strongly agree', and finally converted to percentages. This transformation means that a self-literacy score of 100% indicates that the participant believes they have a very strong understanding of AI. This was visualized through a contingency table in Figure 2. The AI test score was also converted into a percentage in Figure 2. This was done by dividing the participant's test score by the maximum possible score of 12.

When analyzing H3, an area chart was created to visualize how different age groups with a moderate AI test score of 33-50% (corresponding to 4-6 points) perceive their own AI competence. Both scores were plotted in the same graph, with age on the x-axis, as shown in Figure 2.

3.4 Reliability and validity

When evaluating the quality of most empirical social research, four commonly used criteria focus on reliability and validity.

Construct validity was used to ensure that appropriate operational measures were identified for the concepts under examination. The pilot test became a crucial part of confirming what was actually tested. Moreover, multiple sources were used, and the thesis was reviewed by a supervisor before finalization. (Bell, Bryman, and Harley, 2019).

Internal validity refers to the extent to which a study can establish that an observed condition directly causes changes in other conditions. Which is difficult in most small theses, the aim was therefore to create some sort of causality rather than conclusively proving a connection. Specific steps were taken in the data analysis chapter, including the use of clear logic models, pattern matching, and explanation building. The discussion further addresses potential rival explanations of the findings to determine whether the findings are reasonable under alternative conditions (Bell, Bryman, and Harley, 2019).

External validity concerns the generalizability of the study's findings beyond the immediate research context. An issue could be the overrepresentation of respondents from the three companies. To broaden our participant pool, it was decided to recruit additional respondents from outside the three companies. The risk of non-random sampling correction is that the thesis's external validity becomes disputable (Bell, Bryman, and Harley, 2019).

Ecological validity: The focus here is whether the thesis's findings capture our respondents' everyday opinions and values. The goal was to design a questionnaire that allowed respondents to behave naturally, rather than respond in ways influenced by the survey setting. The questionnaire was therefore pilot-tested to ensure that responses reflected participants' honest opinions rather than artifacts of the survey process. (Bell, Bryman, and Harley, 2019).

Reliability: The primary objective of reliability is to ensure that future researchers can replicate the study with ease and achieve consistent findings and conclusions. This has been addressed by explicitly documenting every procedure in detail, thereby enabling replication (Bell, Bryman, and Harley, 2019).

3.5 Ethics, GDPR, and the use of AI

3.5.1 Ethics

According to Bell, Bryman, and Harley (2019), the four main ethical considerations in research are ensuring that participants are not harmed, obtaining informed consent, protecting participants’ privacy, and avoiding deception. To ensure that no participants felt deceived, we clearly stated the study's purpose and how their responses would be used. The respondents were also informed that submitting the survey constituted their consent to participate in the research.

Additionally, the study emphasized that all respondents would remain anonymous and that only limited personal information, specifically age, would be collected in order to safeguard participants’ privacy. Moreover, self-evaluating one’s own work can be considered a sensitive matter. By anonymizing the data, the study ensured that no participant would have their personal or sensitive information disclosed.

3.5.2 GDPR

The EU’s GDPR policy states that individuals whose personal data is being processed have specific rights that must be upheld. In this thesis, careful steps were taken to ensure that none of these rights were violated (IMY - Swedish Authority for Privacy Protection, 2025).

By including an email address for participants to request assistance or ask questions about how their responses would be used, clearly stating the survey's purpose, and anonymizing all collected data, we ensured that no personal information was processed in a way that violated the GDPR.

3.5.3 AI use

In this thesis, AI services, primarily ChatGPT and Perplexity AI, were used as supportive tools during the writing process. The use of the AI services was limited to improving prose clarity, language, and grammar. Further, AI tools were used for brainstorming ideas and to gain a broader understanding of the topic, primarily by recommending relevant articles and suggesting the structure of the thesis. All generated output has been carefully analyzed and reviewed to ensure correct use in relation to LUSEMS (2025) general guidelines and our own academic integrity. The output has therefore only been used as a support for improvements within the thesis, where all the decisions and considerations, for instance, regarding analytical content, empirical findings, and theoretical interpretations, have been made by the authors.

Lastly, AI was used to assist in creating the Python code for graphs and ordinal logistic regression calculations. The prompts are located in the appendix under 8.2. *Central AI prompts.* In line with the course recommendations, as it is primarily concerned with technical and mathematical implementation rather than analytical interpretation, which we haven't or superficially been tested upon in preparatory courses. The use and appropriateness of the AI usage were discussed with the supervisor throughout the writing of this paper, in order to ensure AI's application remained in accordance with the course guidelines.

3.6 Methodological critique

Our theoretical perspective highlights AI use during schooling as a possible explanation for why younger professionals use AI more than their older peers. However, our survey does not include questions specifically addressing respondents' use of AI during their school years. Instead, we asked, "When did you start using AI?" and compared this with the year respondents began using AI in their professional roles. While this allows us to determine whether pre-professional AI experience is linked to workplace AI usage, it does not capture whether AI usage in school itself is an influencing factor.

Another factor that may have influenced the results is that the three companies where the majority of respondents were employed demonstrated strong support for employees' use of AI to optimize workflows. Moreover, these companies have provided substantial AI training to their employees in recent years.

As students of economic sciences, our expertise does not lie in psychology. Therefore, our interpretation of the constructs ATU, SN, and PBC is grounded in the presented literature. The survey questions were designed to capture key dimensions of these constructs and to assess their relationship with age and AI usage. To ensure clarity and relevance, the questions were reviewed by three people in a pilot test. However ideally, the interpretations would have been validated by a psychology expert, but such expertise was unavailable during this study.

The AI literacy test conducted had some limitations. During data collection, it became apparent that some questions were too easy, leading most respondents to score either 3 or 2 points on each question. Although the aim of the questionnaire was to gain a meaningful understanding of respondents' AI literacy, achieving fully reliable results is challenging when using a multiple-choice format.

The answers from our survey were categorized according to the divisions outlined in Chapter 3.3, *Data Collection*, and further segmented by age groups. The distribution across age groups was asymmetrical, with a disproportionately high number of responses from participants aged 20-29. Because most of our responses came from distributing the survey to the three selected organisations as a whole, we had limited control over who chose to participate. Additionally, the title of our survey, "AI Use in Different Age Groups," may have discouraged professionals who do not use AI from participating, thereby affecting the distribution of respondents. Furthermore, the overall lack of respondents in the 60+ age group limited the thesis's ability to examine actual differences in confidence and AI usage across broader age groups, an aspect that could have been explored further.

4. Results and analysis

4.1 Data collection

Age interval	Respondents	% of total
20-29	41	43.16%
30-39	30	31.58%
40-49	15	15.79%
50-59	9	9.47%
Total	**95**	**100.00%**

Table 4: Respondent Age Distribution

Table 4 presents a frequency table showing the number and percentage of respondents in each age interval. A total of n = 95 respondents across four age intervals ranging from 20 to 59 years. The distribution is skewed toward younger respondents, with the largest proportion in the 20-29 group (43.16%), followed by the 30-39 group (31.58%). The two older age groups, 40-49 and 50-59, account for about one-quarter of the sample. Meaning younger professionals are overrepresented in the sample. However, the average respondent's age in our study was 34.7 years, which is around the middle of the age span we analysed (20-59). The skewness is expected and supported by the findings of Grotti et al. (2018), who found that certain industries exhibit an uneven distribution of younger workers. This indicates that, despite the skew towards younger age groups, the sample still includes respondents across a relatively broad age span, allowing age-related patterns to be indicated within the analysis.

Age interval	20-29	30-39	40-49	50-59
		% of total		
AI usage (5.1)				
Use AI daily at work	56,1%	50,0%	60,0%	33,3%
Use AI weekly at work	31,7%	36,7%	26,7%	22,2%
Use AI monthly at work	4,9%	3,3%	0,0%	0,0%
Use AI on rare occasions at work	7,3%	6,7%	13,3%	33,3%
Never use AI at work	0,0%	3,3%	0,0%	11,1%
Feels confidence in work related AI outputs (5.2)				
Do not agree at all	2,4%	0,0%	0,0%	11,1%
Somewhat disagree	9,8%	10,0%	13,3%	33,3%
Not Sure	9,8%	3,3%	20,0%	22,2%
Partly agree	63,4%	76,7%	66,7%	11,1%
Completely agree	14,6%	10,0%	0,0%	22,2%
Feel capable of using AI to enhance work efficiency (5.3)				
Do not agree at all	0,0%	0,0%	0,0%	33,3%
Somewhat disagree	2,4%	13,3%	20,0%	0,0%
Not Sure	12,2%	10,0%	6,7%	22,2%
Partly agree	56,1%	43,3%	46,7%	11,1%
Completely agree	29,3%	33,3%	26,7%	33,3%
AI Literacy score (5.4)				
Minimal AI Knowledge 0-3	9,8%	6,7%	13,3%	44,4%
Some AI Knowledge 4-6	24,4%	23,3%	33,3%	22,2%
Good AI Knowledge 7-9	39,0%	43,3%	20,0%	11,1%
Strong AI Knowledge 10-12	26,8%	26,7%	33,3%	22,2%
Started using AI at work (5.5)				
Before 2020	0.0%	0.0%	6.7%	0.0%
2021	11.6%	3.0%	0.0%	0.0%
2022	34.9%	15.2%	6.7%	0.0%
2023	27.9%	48.5%	33.3%	11.1%
2024	14.0%	24.2%	53.3%	55.6%
2025	11.6%	9.1%	0.0%	33.3%
AI for personal use (5.6)				
Use AI daily	48,8%	43,3%	33,3%	33,3%
Use AI weekly	36,6%	36,7%	66,7%	22,2%
Use AI monthly	7,3%	13,3%	0,0%	11,1%
Use AI on rare occasions	4,9%	6,7%	0,0%	22,2%
Never use AI	2,4%	0,0%	0,0%	11,1%

Table 5. Contingency table showing the percentage differences in the prevalence of different responses.

Table 5 presents the descriptive statistics illustrating the percentage distribution of response options selected by respondents across age groups. The results are presented as individual graphs named 5.1.1-5.6.1 in the appendix chapter 7.5 Analysis.

Table 5.1 and Graph 5.1 illustrate AI usage at work. The results indicate that professionals aged 20-29 were not the heaviest users of AI in terms of daily usage. Instead, the highest proportion of daily AI use at work is among respondents aged 40-49, with 60% reporting daily use. Labeling both daily and weekly usage as frequent usage and subsequently infrequent AI usage as "monthly", “occasional”, and “non-existent” usage across age groups. A homogeneous trend appears among respondents aged 20-49, with 87.8% in the 20-29 age group using AI frequently, to 86.7% in the 30-49 age group. There’s a steep decline in frequent AI use in a work setting among the 50-59 age group, down to 55.5%. Hence, a clear indication of the decline in usage associated with age is first apparent in the age group 50-59.

Table 5.2, with Graph 5.2.1, illustrates the differences in confidence in work-related AI output across different age groups. Responses classified as ‘do not agree at all’ and ‘somewhat disagree’ were combined to represent low confidence, while ‘not sure’ was treated as a separate category, and ‘partially agree’ and ‘completely agree’ were combined to reflect high confidence. The findings reveal that confidence is highest among respondents aged 30-39, with 86.7% reporting high confidence and the least amount of low confidence. Respondents aged 20-29 also demonstrate high confidence at 78%, though they exhibit slightly greater uncertainty than the 30-39 group. Hence, confidence tends to decline in the older age bracket after age group 20-39, with the lowest levels observed among respondents aged 50-59.

Table 5.3, with Graph 5.3.1, illustrates the perceived ability to use AI to enhance work efficiency by age group. Respondents were classified accordingly to Graph 5.2.1. The results indicate a gradual decline in perceived ability to use AI to improve their work efficiency. High perceived ability is most common among the age group 20-29, with 85.4% partially or completely agreeing that they are capable of using AI to enhance their work efficiency. In parallel, the lowest level of high perceived ability is observed in the 50-59 age group, where only 44.4% report high perceived capabilities. Accordingly, perceived ability decreases with age: one-third of respondents aged 50-59 do not agree at all that they are capable of using AI to enhance work efficiency, whereas no respondents in the younger age groups reported complete disagreement, further contributing to the observed decline in perceived ability.

Table 5.4 with Graph 5.4.1 illustrates the AI literacy score. The findings indicate that younger age groups, specifically those between 20-29 and 30-39, show similar percentages across literacy groups, with only minor differences. Most professionals in the 20-39 age group fall into the “good” (7-9) or “strong” (10-12) knowledge categories, with minimal AI literacy relatively uncommon, comprising less than 10% of respondents. Additionally, around 25% of professionals possess “some” AI literacy across all age groups, with younger professionals exhibiting a slightly higher percentage of minimal and some AI literacy. In contrast, the 40-49 age group shows a more varied distribution of AI literacy. Within this demographic, approximately one-third demonstrate strong AI knowledge. Another third falls within the “some AI-knowledge” category, indicating a shift away from younger age groups. The trend shifts when examining the 50-59 age group. This demographic displays the lowest overall AI literacy levels. This Age group shows the highest share of minimal AI literacy, accounting for 44.4% of respondents, alongside comparatively lower representation in the good and strong AI quartiles.

Table 5.5, with Graph 5.5.1, illustrates the year professionals began using AI by age group. Younger respondents aged 20-29 show a clear pattern of earlier AI adoption. 46.5% reported starting to use AI in 2022 or earlier. In comparison, 18.2% of respondents aged 30-39 and 13.4% of those aged 40-49 reported similarly early adoption, while none of the respondents in the 50-59 age group began using AI in 2022 or earlier. Age group 30-39, the largest proportion reports having started using AI in 2023, and among respondents aged 40-49, the largest proportion started using AI in 2024, however, 40-49 is the only age group that included respondents who started using AI before 2020. The latest adoption is observed among respondents aged 50-59, with 55.6% starting to use AI in 2024. Overall, the results show a clear shift toward later AI adoption with increasing age.

Regarding AI use for personal purposes, 5.6 and Graph 5.6.1 illustrate the frequency of AI usage outside a work-related context across age groups. The results show that AI use for personal purposes is common across all age groups, with a majority of respondents reporting weekly or more frequent use. Amongst respondents aged 20-29 and 30-39, almost half report daily AI use for personal purposes, while respondents aged 40-49 display the highest proportion of weekly AI usage, whereas respondents aged 50-59 show a more spread pattern of personal AI usage, with a lower share of of frequent usage and more common infrequent or no usage compared to younger age groups.

Ages	20-29	30-39	40-49	50-59
AI Literacy Score	7,5	7,5	7,5	4,7
Self literacy score	9,9	10,2	10,6	12,3

Table 6: Contingency table showing the relationship between age and AI

Table 6 presents descriptive index measures across age groups and the relationships among the stated variables, in relation to the theories, categories, and age. In line with the analytical approach outlined in section 3.3.2.3. The table shows the average AI literacy score. The variable self-literacy score is presented as inverted scores, with lower values indicating greater agreement with the cluster of questions summarized in Table 3 in Appendix 8.3 Methodology.

Regarding the AI-literacy score, the average indicates that measured AI-literacy remains stable among respondents aged 20-49, while a notably lower score is observed among respondents aged 50-59. In comparison, the self-assessed AI literacy score shows a wider spread of results, as perceived confidence decreases with age. This is further contextualised by Figure 2:

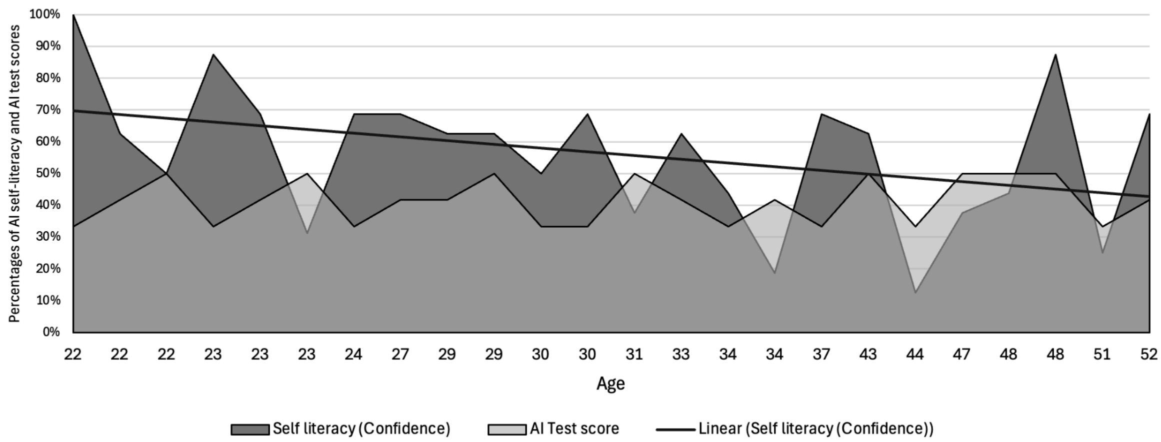


Figure 2: Self-perceived AI literacy vs. AI literacy

Figure 2 illustrates the relationship between respondents with some understanding of how AI works and their confidence levels. As defined in 3.3.1, some understanding corresponds to scoring between 33.3% and 50% of the total points on the AI literacy test, that is, 4-6 points. The self-assessed literacy score was constructed so that 100% represents the maximum perceived AI literacy. The results show that average confidence declines with age among respondents who demonstrate some understanding of AI, as illustrated by the trendline. This suggests that younger respondents with comparable levels of AI literacy exhibit greater confidence in their AI-related abilities than older respondents with the same level of understanding.

Hypothesis	**Category**	**β**	**std_err**	**P-value**	**Result**
H1	Professionals use of AI tools	-0.0347	0.0196	0.08	Not supported
	Private use of AI tools	-0.0383	0.0197	0.05	**Supported**
H1a	Earlier AI exposure influences workplace AI usag	-0.0378	0.0198	0.06	Not supported
H1b	Benefits outweighs the costs	0.0162	0.0171	0.34	Not supported
H1c	AI tools are necessary to keep up with workload	0.0040	0.0177	0.82	Not supported
H1d	AI use increases risk of incorrect or misleading information	0.0157	0.0188	0.40	Not supported
H1e	Perceived need to use AI to stay relevant in the job market	0.036	0.0189	0.06	Not supported
H1f	AI use is influenced by peers and managers	0.0037	0.0172	0.83	Not supported
H1g	Fear of negative peer and managerial perceptions from AI use	0.0716	0.0197	0.00	**Supported**
H1h	Self preceived ease to implement AI in work	0.0042	0.0176	0.81	Not supported
H2	Confidence in AI output	0.04	0.0202	0.05	**Supported**
H2a	Self preceived AI skills and knowledge	0.03	0.0185	0.11	Not supported
H2b	Support of decision making	-0.0087	0.0183	0.64	Not supported
H2c	Understanding of AI	0.0354	0.019	0.06	Not supported
H3	Age & Score vs Confidence	-0.0127	0.0059	0.03	**Supported**

Table 7: Ordinal Logistic Regression with predicting variable Age determining interlinkage between usage, ATU, SN, PBC, confidence & knowledge.

Table 7 presents the results of the ordinal logit tests conducted for the different hypotheses and for the relationship between age and private AI use. Results with a p-value below 0.05 are considered statistically significant. Furthermore, private use of AI tools H1, H2, and H3 is supported, and therefore, the null hypotheses are not supported. The remaining hypotheses were all rejected in favor of the null hypothesis.

Deriving from Table 7, the following conclusions are drawn: younger respondents use AI more frequently for personal purposes than older respondents. This pattern is further illustrated in Graph 5.6.1, which contrasts with H1, in which the null hypothesis cannot be rejected. Furthermore, Table 7 supports the finding that younger respondents are more concerned about how peers and managers perceive them when using AI. The null hypothesis can be rejected in favour of H1g. In addition, for H2, the null hypothesis is rejected, as statistical significance is found, indicating that younger respondents have higher confidence in work-specific AI-generated outputs.

Finally, H3 is supported by analyses of age, AI-litteracy score, and confidence, which show that respondents' confidence in work-related AI-generated outputs decreases with age. Hence, we can reject the null hypothesis in H3.

4.2 Analysis of H1-H1g & private usage of AI

When examining whether age is negatively related to professionals' use of AI tools, Table 7 shows that H1 is not supported by the data. Instead, from the descriptive statistics shown in Graph 5.1.1, as age increases, there is no obvious shift in the probability of more frequent AI use at work. Furthermore, the overall effect of age on usage does not have a p-value that indicates statistical significance. These findings contradict those of Morris and Venkatesh (2000), who reported that technology use is more frequent among younger professionals. They are also in contrast with Koning and Gelderblom's (2006) argument that older professionals may use ICTs less often because they find learning new systems more difficult than younger professionals, as well as more recent findings by Aramali et al. (2025), who observed that AI adoption is generally higher among younger professionals. Moreover, it contradicts the findings of KPMG together with the University of Melbourne (2025), who showed that younger professionals used AI more frequently than their older peers. Furthermore, the results do not support Morris and Venkatesh's (2000) findings, as no statistically significant relationships were found between Age, Usage, ATU, or PBC. Thus, one can not reject the null hypothesis in H1a, H1b, H1c, H1d, H1e, or H1f.

In contrast to the rejection of H1, Table 5.6 shows that private use of AI was more frequent amongst younger respondents. Although H1e was not statistically significant, a p-value of 0.06 suggests a possible pattern in which younger professionals perceive AI as important for staying relevant in today's job market, as shown by Xu et al. (2024). This may suggest that younger professionals are more influenced by ATU, as Morris and Venkatesh (2000) proposed**.**

The support of H1g contradicts the findings by Morris and Venkatesh (2000), with a p-value of .0003. Our findings suggest that younger professionals worry more that the use of AI may negatively influence how peers and managers perceive them compared to older professionals. Interestingly, Table 5.5 shows that older professionals adopted AI later than their younger counterparts. As noted in Section 3.6, the majority of respondents worked within organisations that actively promoted AI usage where efficiency gains could be achieved. This could align with Morris and Venkatesh (2000), as older professionals may have started using AI later, possibly once management promoted its use, and were therefore still more affected by SN. However, if this had been the case, one would have expected H1f not to be rejected. Instead, with a p-value of 0.83 for H1f, which examines the effect of age on SN, the null hypothesis could not be rejected.

4.2.1 Analysis of Private Usage of AI

Descriptive statistics on professionals' private AI usage are presented, even though they are not included in *Figure 1: Connection between hypothesis and survey questions*. The inclusion is backed by the insight it contributes. The data indicates that at least 55.5% of respondents across all age groups use AI weekly for personal purposes. The oldest respondents appear to use AI more frequently for personal purposes than for work-related tasks, while respondents aged 40-49 report slightly higher AI usage at work than in their private lives. Using an ordinal logit model, the test yielded a p-value of 0.05. The null hypothesis cannot be rejected, indicating that younger professionals use AI for personal purposes more than their older peers. The statistically significant results are consistent with the findings of Xu et al. (2024).

4.2.2 Analysis of H2-H2c

When analysing whether H2*: Age is negatively interrelated to the confidence in work-specific AI-generated output,* the results indicated a statistically significant p-value of 0.05. This suggests that age negatively affects professionals' confidence in AI-generated output. The Dunning-Kreuger effect (1999) presents an analytical perspective on the overestimation of one's ability to evaluate correctness. The decreased confidence with age suggests that the older you get, the more knowledge you have, hence, your confidence level decreases, and/or you become aware of your lack of knowledge, which indicates accurate self-assessment (Dunning & Sanchez, 2018). This suggests that younger individuals are more likely to be at the peak of miscalibrated confidence than older individuals in a professional setting. The reasoning, therefore, follows the findings of Xu et al. (2024), who argue that younger people's experience of working under time pressure, combined with demands for efficiency and a desire for convenience, leads them to place strong trust in AI outputs. Further expanding on Chong's (2022) finding that AI-confidence is secondary to individuals' self-confidence, this study provides a plausible explanation for the affirmation of the hypothesis.

However, the non-significant outcomes of the sub-hypotheses, formulated to explore the potential sources of confidence, provide important nuance to the interpretation of H2. The non-supported H2a indicates that younger professionals' confidence cannot be explained by higher perceived skills or knowledge related to using AI for efficiency gains. The lack of support for H2b suggests that younger individuals do not rely on AI to a greater extent than older professionals when supporting decision-making in their line of work. Further, the non-supported H2c suggests no relationship between age and perceived understanding; although not significant, the P-value indicates a directional association towards greater understanding of younger professionals, as shown in Table 7.

The non-supported sub-hypothesis, therefore, appears to operate independently of AI-specific factors. This contrasts with the findings of Guan et al. (2024) and Horowitz and Khan (2024), who identified a relationship between technological knowledge and perceived self-ability. The results suggest that observed differences in confidence cannot be attributed to AI-specific competence or understanding. Instead, confidence appears to be shaped by factors related to professional maturity and accumulated experience. Accordingly, older professionals may express lower confidence not because of limited understanding, but because of greater awareness of uncertainty, limitations, and the potential consequences of incorrect decision-making, as well as more profound domain expertise, consistent with Kahneman and Klein (2009).

4.2.3 Analysis of H3

When analysing whether H3*: Confidence in work-specific AI-generated outputs among individuals with lower AI-knowledge decreases with age*. The results indicated statistical significance (p-value = 0.03). The finding aligns with the reasoning in 4.2.2 and further strengthens the result that confidence in AI-generated output decreases with age. Younger professionals have higher confidence in work-related outputs than older professionals with the same level of AI knowledge. The increasing trend in self-literacy scores can be seen in relation to the previous reasoning of Dunning & Kruger (1999) in 4.2.2, where younger professionals are placed higher on the Dunning-Kruger curve, indicating overconfidence in one's abilities. While older individuals are placed either before the peak of the Dunning-Kruger curve, showing greater self-assessment due to a lack of knowledge, as suggested by Dunning & Sanchez, or after it, indicating an increase in knowledge within the relevant subject and a lack of confidence inflation, compared to younger professionals.

Due to the subhypothesis in H2 being rejected, and, naturally, the AI-related line of reasoning regarding confidence in usage was rejected. The finding, therefore, aligns with Kahneman and Klein's (2009) research, which suggests that professionals with greater experience are more likely to be aware of their own limitations and therefore demonstrate a more accurate assessment of their knowledge.

Taken together, the hypothesis could be supported, older professionals with the same level of knowledge show less confidence in AI-specific work outputs, and this is better explained by age-related differences in confidence rather than differences in AI literacy or usage. This analytical finding also complements the H2 result and further contextualises the role of age as an indicator of experience in professional contexts, thereby serving as a differentiating factor in confidence.

5. Discussion

This thesis aimed to provide a better understanding of age-related differences in professionals' use of AI and their confidence in AI-generated outputs. To achieve this, three main hypotheses were formulated, along with sub-hypotheses designed to provide further insight into age-related differences in professionals' AI usage.

5.1 Discussion: Age as a factor in AI use amongst professionals

When analysing H1, which proposed that age is negatively related to professionals' use of AI tools, the hypothesis was rejected because no statistically significant relationship was found between age and AI use at work. The finding contrasts with the results reported by Morris and Venkatesh (2000). One possible explanation for the rejection of H1 is that Morris and Venkatesh (2000) examined newly implemented technology within organisations over a five-month period. Hence, it's important to note that our respondents reported using AI at work for several years, whereas only a minority began using AI for professional work in 2025. Thus, one reason for our rejection of H1 is that the effect of age on usage diminishes over time. Another reason this thesis may not have been able to replicate earlier findings on the effect of age on usage could be the specific set of companies from which the majority of the data were collected. In contrast to our rejection of H1, other research presented in this thesis found that AI use was more frequent among younger respondents, suggesting that the underlying reason for H1's rejection may be the companies the majority of respondents worked for. The three organisations from which the majority of respondents were drawn all had educational programs on AI use, as well as strong overall support for AI within their organisational cultures. The implementation of AI within these organisations may make it difficult not to utilize AI in work-related tasks; however, older respondents were less inclined to use AI for personal purposes on a daily basis, as shown in tables 6.6 & 8. The lower use of AI for personal purposes may stem from the absence of external organisational pressures to encourage its use. As a result, when older respondents had the option not to use AI, they were more likely to refrain at the same frequency.

That said, the descriptive statistics presented in Table 5 indicate that younger professionals adopted AI earlier than their perhaps more change-averse older peers, consistent with the theoretical perspectives proposed by Aramali et al. (2025). However, as most respondents worked in organisations where AI is deeply embedded in everyday work practices, it is reasonable to assume that the results reflect the professionals' organizational context. Accordingly, the findings might have differed if the survey had been distributed to organisations with no active AI focus or to organisations that had only recently begun implementing AI. As an analogy, both diamonds and coal are composed of the same material: carbon. However, if one were to assess the hardness of carbon using a quantitative analysis of a dataset combining diamonds and coal, the results would likely show no statistically significant difference in hardness. Consequently, all sub-hypotheses of H1 were rejected, except for H1g, which states that despite AI being used to a similar extent across all age groups, younger respondents fear judgment from peers and managers to a greater extent than older respondents. Our survey did not capture the underlying reasons why younger professionals feared judgment. One possible explanation is that the confidence observed in H2 led them to believe that their abilities would not be fully understood or recognised by their managers and peers, but instead interpreted as an inability to solve tasks independently.

Furthermore, it's worth mentioning that the survey questions, and consequently, our analysis, did not capture the full scope of respondents' AI usage. For example, a respondent who uses AI 30 times per day and a respondent who uses AI only once per day would be placed in the same usage frequency category. Had it been anticipated that AI usage would be so similar across age groups, as observed in the dataset, a different survey question structure would have been preferred to more accurately capture respondents' actual levels of usage. At the same time, the lack of support for H1 contradicts the theoretical perspectives on technology adoption and use presented in Section 1.2: Research Problem. Even so, our results from the sample of n = 95 convey a clear message: using AI has become the norm for most professionals, and this use occurs both at work and outside of it.

5.2 Discussion: Age is negatively interrelated to confidence

The results supporting H2 align with prior research showing that younger individuals have higher confidence in AI (XU et al., 2024). EY (2024) similarly suggests that younger age groups may exhibit high confidence in AI despite a weaker ability to assess the correctness of its output. However, the findings that appear to diverge from the Dunning-Kruger-related conclusions presented by Fernandes (2026) should not be interpreted as contradictory.

Fernandes's work differed as the research was conducted in experimentally controlled task settings, focusing on metacognitive accuracy. In contrast, this thesis focuses more on age-related and with an organizational approach. The findings should therefore be understood as complementary rather than conflicting.

One interpretation of the results is that younger professionals may be more inclined to view AI as a competitive advantage (XU et al., 2024) and hence show greater confidence in its output, while older professionals may associate AI more strongly with the risks of role replacement. Although this generational perception of AI's relevance could not be statistically confirmed, the results for H1e suggest that younger professionals tend to see AI as more important for remaining competitive in today's job market.

The rejection of all H2 sub-hypotheses indicates that the thesis did not identify the source of confidence beyond age. Based on Guan et al. (2024) and Horowitz and Khan (2024), confidence was expected to stem from higher AI usage and greater perceived technological competence. A likely reason for the divergence from earlier findings is the study context, this thesis uses a heterogeneous sample, unlike the student sample in Guan et al. (2024) or the specialized international security population in Horowitz and Khan (2024). Moreover, those studies are nearly two years old and were published the same year that many respondents aged 40–59 in this study began using AI, so rapid changes in AI adoption may limit comparability. Another likely explanation is the absence of clear generational differences in usage. Contrary to prior studies, H1 was not supported, indicating that younger professionals did not use AI significantly more than older ones. This challenges the assumption that confidence is primarily driven by usage intensity. With similar usage across age groups, the H2 sub-hypotheses could not capture the expected differences in perceived technical ability and confidence. This pattern suggests that confidence is more of a psychological or organizational phenomenon than a purely technological one, changing with age independently of usage and perceived competence.

By contrast, the confidence pattern among older professionals aligns more closely with the hypothesis formulation that confidence is shaped by accumulated professional experience. Lower stated confidence among older professionals may reflect heightened awareness of the limitations, uncertainty, and flaws of AI-generated output. Their experience may make them more alert to potential errors, resulting in lower expressed confidence. This is further supported by H3, indicating that other factors, such as work-related factors, provide an interpretation of where the confidence derives. This interpretation fits the results and the theoretical framework. It should be emphasised that the thesis does not directly test respondents' specific knowledge or expertise across industries or decision-making situations. This is a limitation. Such testing was considered but deemed too broad and complex for the study's scope. Survey questions would likely have captured subjective perceptions of decision-making rather than objectively measured expertise, and designing comparable objective measures across sectors would have been difficult. Including such measures would have broadened the study while reducing the precision of its analytical contribution.

This reliance on self-assessments is already evident in the thesis, as the rejection of the H2 sub-hypothesis and the support for H3 suggest that confidence may be influenced by factors beyond AI-related competence or professional experience. Confidence may instead be shaped by general self-confidence, risk tolerance, or organizational role, such as whether an individual holds an entry-level position or a senior role with greater responsibility and, consequently, a lower tolerance for errors.

Accordingly, the conclusion that age-related differences in confidence derive from experience rather than AI-specific competence should be understood as an analytical interpretation, not a statistically demonstrated causal relationship. It also points to the plausibility of psychological, social, and organizational explanations, and highlights the need for further research on what drives AI usage and decision-making in organizational settings.

5.3 Organisational implications of the research findings

The relationship between age and confidence is of particular interest to organisations implementing AI, as age differences may influence AI adoption. As stated, employees who lack trust in AI may fear being replaced, which can impede adoption. The findings of this thesis indicate that older professionals use AI to a similar extent as younger professionals and that there is no correlation with age in professionals' belief that its benefits outweigh its costs. Together with younger professionals' strong AI confidence, this is encouraging for organisations with an ambition to adopt AI, as they may be more willing to incorporate AI at work.

Despite these positive outcomes, certain risks persist. As established in section 5.2, younger professionals tend to be closer to the peak of miscalibrated confidence. In addition, younger professionals report greater fear of judgment than their peers while simultaneously exhibiting higher confidence in AI outputs. This suggests that professionals may hesitate to use AI openly, while still expressing high confidence in AI-generated content when they do rely on it. Such a combination may lead to underutilisation of AI or, when used, an increased risk of errors due to overreliance. However, the thesis does not claim that younger professionals misjudge AI output; rather, it argues that confidence appears elevated relative to age and experience.

Nevertheless, a central question remains unanswered and prevents full conclusions, which falls beyond the scope of the present study: at what level of confidence is the appropriate level for AI output? Regarding Hypothesis 3, the higher confidence observed among younger professionals with lower AI knowledge may reflect automation bias and highlight "accountability gap" challenges in AI adoption. Previous cases at organisations such as Amazon and Deloitte demonstrate that excessive trust in automation can lead to undesirable outcomes. Overcalibrated confidence, therefore, can be naturally excluded from the above dilemma of what the right amount of confidence is. While older professionals exhibit more accurate confidence in their competence, their lower confidence may slow AI adoption and reduce perceived benefits. Overall, these findings suggest that organisational challenges in AI adoption are partly age-related, as older users' challenges align with trust, while younger users' align with critical evaluation. Understanding these differences can help organisations manage AI implementation more effectively, balancing confidence, critical thinking, and adoption rates across age groups.

6. Conclusion

This thesis aimed to enhance the understanding of age-related differences in professionals' AI usage and confidence. Due to the distribution of participants, drawing fully generalisable conclusions proved challenging. In the sample, no significant relationship between age and AI use at work was identified. This may be explained by the fact that a large share of respondents were employed in organisations with a strong AI culture, high levels of AI implementation, and active AI education, which likely reduced age-related differences in workplace usage. Younger participants reported greater concern about being judged by managers and peers for using AI. Despite this, younger professionals exhibited higher confidence in AI outputs than older professionals, regardless of their actual AI literacy. Younger professionals' heightened fear of judgment and tendency toward overconfidence may hinder effective use or increase the risk of overlooked errors.

Importantly, this thesis could not conclusively determine the source of this overconfidence, as all sub-hypotheses related to H2 were rejected. A plausible explanation is that accumulated professional experience enables older professionals to develop a more calibrated assessment of their own abilities. The findings further suggest that individuals with some AI literacy and higher age tend to assess their competence more accurately, while younger professionals with some AI knowledge are more prone to overestimating their abilities.

For organizations seeking to understand age-related differences in AI use, our findings suggest that overall AI use does not differ significantly across age groups. However, age does appear to shape how professionals trust AI outputs. Challenges in AI adoption may therefore be age-related. Older professionals tend to trust AI less than younger professionals, and younger professionals report stronger fears of being judged by managers and peers. Organizations can address this by fostering an environment in which AI use is normalized and supported, while simultaneously promoting critical evaluation of AI outputs to reduce the risks associated with uncritical reliance.

7. Suggestions for Future Research

Since the effect of age on technology use has been demonstrated in previous studies, future research could investigate whether this effect diminishes over time, especially in AI use. Other promising avenues for future research include examining potential differences in the quality of AI-generated output across age groups. Given the significant age-related differences in confidence, future studies exploring whether the quality of AI output varies across professionals of different ages would be highly relevant. Such differences, which our study does not account for, may also introduce noise or bias into AI-assisted work outcomes, effects that could be further researched. It is important to note that, on average, respondents have used AI over the past three years. Therefore, it would be highly relevant for future research to conduct a similar study in 10 years' time to assess generational differences in AI usage, when the youngest professionals will have been exposed to AI for most of their lives.

8. Appendix

8.1 Survey options and their numerical values for analysis

Survey option	Numerical value
I completely agree	1
I partly agree	2
I'm not sure / I do not have an opinion	3
I somewhat disagree	4
I do not agree at all	5
0-5 years	5
6-12 years	4
13-20 years	3
20-30 years	2
30+ years	1
A	1
B	2
C	3
D	4
E	5
Daily	5
Weekly	4
Monthly	3
On rare occasions	2
Never	1

Before / pre 2020	6
2021	5
2022	4
2023	3
2024	2
2025	1

Table 8: Survey options and their numerical values for analysis

8.2 Central AI prompts

We are trying to answer the following hypothesis:

Hypothesis Question

H1 Age is negatively interrelated to the use of AI tools

H1a Previous exposure of AI affects younger professionals AI usage in their line of work

H1b ATU is interrelated with age

H1c Agreement of necessity to use Ai tools in order to keep up with workload

is interrelated with age

H1d Agreement that using AI increases the likelihood of incorrect or misleading information is interrelated with age

H1e Agreement of necessity to use ai in order to stay relevant in today's job market is interrelated with age

H1f Agreement with the statement that the use of AI for work tasks is influenced by peers or managers is interrelated with age

H1g "Agreement with the statement that AI use

may negatively influence how peers and managers perceive the respondent is interrelated to age.

H1h Agreement to the statement that AI usage is easy to implement in my line of work is interrelated to age

H2 Age is negatively interrelated to the confidence in work specific AI-generated output

H2a Younger indivudals report higher levels of percived skills and knowledge to use for increasing effciency

H2b Younger indivudals rely more on AI to support decision-making in their line of work

H2c Younger indviduals report higher perceived undersanding of how AI systems, algorithms, and data models function

H3 Age and low knowledge is negatively interrelated to the confidence in work specific AI-generated output

The survey questions we have are:

What is your age? - The respondents age - connected to all hypothesis

How often do you use AI in your line of work? - answer option 4 - connected to H1

When did you start using AI? - Answer option 5 - connected to H1a

When did you start using AI in your line of work? Answer option 5 connected to H1a

How often do you use AI for personal use answer option 4 - not connected to a hypothesis, byt check if age is related to personal AI usage.

I have confidence in the output generated by AI systems for my line of work. Answer option 1 - connected to H2 & H3

I have sufficient skills and knowledge to increase efficiency in my line of work through the use of AI. Answer option 1 - connected to H2a

I rely on AI to support my decision-making in my line of work. Answer option 1 - connected to H2b

I believe I understand how AI systems work, in regards to underlying algorithms and data models that shape AI decisions and outputs. Answer option 1 - connected to H2c

I am of the opinion that the benefits of using AI in my line of work outweigh the downsides Answer option 1 - connected to H1b

I find it necessary to use AI tools to keep up with my workload. Answer option 1 - connected to H1c

I believe that using AI increases the likelihood of incorrect or misleading information in my line of work. Answer option 1 - connected to H1d

My use of AI for work tasks is influenced by my peers or managers. Answer option 1 - connected to H1f

I worry that my use of AI may negatively influence how peers and managers perceive me. Answer option 1 - connected to H1g

I feel its necessary to stay up to date with AI technologies to remain competitive in today's job market. Answer option 1 - connected to H1g

I feel that AI usage is easy to implement in my line of work Answer option 1 - connected to H1h

Score = just the accumulated score 0-12 from some knowledge questions, higher = better - connected to H3

Survey option - Numerical value

Answer option 1:
I completely agree — 1
I partly agree — 2
I'm not sure / I do not have an opinion — 3
I somewhat disagree — 4
I do not agree at all — 5

Answer option 2:

0-5 years — 5
6-12 years — (value not shown due to dropdown arrow)
13-20 years — 3
20-30 years — 2
30+ years — 1

Answer option 3:
Daily — 5
Weekly — 4
Monthly — 3
On rare occasions — 2
Never — 1

Answer option 4:

Before / pre 2020 — 6
2021 — 5
2022 — 4
2023 — 3
2024 — 2
2025 — 1

Create a ordinal logit python code that tests our hypothesis. All except H3 are Age impact on X. For H3, take Age, score and numerical value from I have confidence in the output generated by AI systems for my line of work. To asses whether age with x score impacts confidence

8.2.1 AI generated prompt used to generate python code

You are a data analyst. I need **Python code** to test several hypotheses using **ordinal logistic regression (proportional odds / ordered logit)**.

Context

We ran a survey about AI use at work. We want to test whether **Age** is related to various ordinal outcomes (usage, attitudes, confidence, etc.).

Variables (survey items) and what they measure

Assume my dataset is a CSV called survey.csv with one row per respondent and these columns (rename in code if needed):

Predictor

- age = respondent age (numeric in years, or an ordered age category; if category, treat as ordered numeric).

Usage / exposure (ordinal)

- ai_work_freq = "How often do you use AI in your line of work?" (Answer option 3)
- ai_personal_freq = "How often do you use AI for personal use?" (Answer option 3; exploratory)
- ai_start_year = "When did you start using AI?" (Answer option 4)
- ai_work_start_year = "When did you start using AI in your line of work?" (Answer option 4)

Attitudes / perceptions (Likert, ordinal; Answer option 1)

- confidence_ai_output = "I have confidence in the output generated by AI systems for my line of work."

- skills_ai_efficiency = “I have sufficient skills and knowledge to increase efficiency in my line of work through AI.”

- rely_ai_decisions = “I rely on AI to support decision-making in my line of work.”

- understand_ai = “I understand how AI systems work (algorithms/data models).”

- benefits_outweigh = “Benefits of using AI in my line of work outweigh the downsides.”

- necessary_workload = “Necessary to use AI tools to keep up with workload.”

- misleading_risk = “Using AI increases likelihood of incorrect/misleading information.”

- peer_manager_influence = “My AI use is influenced by peers/managers.”

- negative_perception_worry = “I worry AI use may negatively influence how peers/managers perceive me.”

- stay_relevant_jobmarket = “Necessary to stay up to date with AI to remain competitive in today’s job market.”

- easy_implement = “AI usage is easy to implement in my line of work.”

Knowledge score

- score = accumulated knowledge score (0-12), higher = better.

Coding

The survey is already transformed into numeric ordinal values as follows:

Likert (Answer option 1):

- completely agree=1, partly agree=2, neutral=3, somewhat disagree=4, not agree at all=5
 (So **lower = more agreement**)

Frequency (Answer option 3):

- daily=5, weekly=4, monthly=3, rare=2, never=1
  (So **higher = more frequent**)

Start year (Answer option 4):

- pre-2020=6, 2021=5, 2022=4, 2023=3, 2024=2, 2025=1
  (So **higher = earlier adoption**)

Hypotheses to test

Use **ordered logit** for each dependent variable. Unless specified, each model is:

DV ~ age

H1: Age is negatively interrelated to the use of AI tools

- Test with DV: ai_work_freq

H1a: Previous exposure affects younger professionals' AI usage

- Use DV: ai_work_freq
- Use predictors: age, ai_work_start_year (and optionally their interaction).
  ("Earlier start year" = higher numeric value)

H1b-H1h: Each attitude item is interrelated with age

- H1b DV: benefits_outweigh
- H1c DV: necessary_workload
- H1d DV: misleading_risk
- H1e DV: stay_relevant_jobmarket

- H1f DV: peer_manager_influence
- H1g DV: negative_perception_worry
- H1h DV: easy_implement

H2: Age is negatively interrelated to confidence in AI-generated output

- DV: confidence_ai_output

H2a-H2c: Younger individuals report higher perceived skills/reliance/understanding

- H2a DV: skills_ai_efficiency
- H2b DV: rely_ai_decisions
- H2c DV: understand_ai

H3: Age and low knowledge are negatively interrelated to confidence in AI-generated output

- DV: confidence_ai_output
- Predictors: age, score, and **age × score interaction** to assess whether age "with x score" impacts confidence.

Output requirements

Produce Python code that:

1. Loads survey.csv
2. Fits ordered logit models for each hypothesis (statsmodels preferred)
3. Prints coefficient tables with standard errors, p-values

4. Includes an interpretation helper: note direction carefully because some scales have “1 = agree” while others have “5 = agree”.

8.2.2 AI-generated prompt used to “brainstorm”, improve text, and grammar.

The following AI prompts were used with ChatGPT in no specific order. The questions have also been translated into English for clarity:

- “Enhance prose and grammar.”
- “Is this part more suitable as problematization or background?”
- “What are the main differences between analysis and results?"
- “Are the hypotheses clear to the reader”?
- “Is this too much analysis to be in the result?”
- “What should a good analysis contain?”
- “Explain the maths behind ordinal logit.”
- “What is high-top level decision-making in organisational contexts?”
- “Explain bounded rationality in simple terms.”
- “Is this part repetitive?”
- “Explain the beta variable in an ordinal logit model.”
- “How much of the theory should be revised in the hypothesis development?”
- “Explain the dunning-kruger curve in simple terms.”
- “Summarise noise and bias”
- “How should I reference this using the Harvard referencing system?”
- “Give 5 examples of how this data could be presented in graphs.”
- “If we have statistical significance, do we reject the null hypothesis?”
- “Does a null hypothesis need to be written out?”
- “Where should I place a dot in the following part?”
- “Could you help us sort these references in alphabetical order?”
- “What's a good synonym for this word?”

8.3 Methodology

Hypothesis	Questions	Category
H1	How often do you use AI in your line of work?	Professionals use of AI tools
H1a	When did you start using AI?, When did you start using AI in your line of work?	Earlier AI exposure influences workplace AI usag
H1b	I am of the opinion that the benefits of using AI in my line of work outweigh the downsides	Benefits outweighs the costs
H1c	I find it necessary to use AI tools to keep up with my workload.	AI tools are necessary to keep up with workload
H1d	I believe that using AI increases the likelihood of incorrect or misleading information in my line of work.	AI use increases risk of incorrect or misleading information
H1e	I feel its necessary to stay up to date with AI technologies to remain competitive in today's job market.	Perceived need to use AI to stay relevant in the job market
H1f	My use of AI for work tasks is influenced by my peers or managers.	AI use is influenced by peers and managers
H1g	I worry that my use of AI may negatively influence how peers and managers perceive me,	Fear of negative peer and managerial perceptions from AI use
H1h	I feel that AI usage is easy to implement in my line of work	Self preceived ease to implement AI in work
H2	I have confidence in the output generated by AI systems for my line of work	Confidence in AI output
H2a	I have sufficient skills and knowledge to increase efficiency in my line of work through the use of AI.	Self preceived AI skills and knowledge
H2b	I rely on AI to support my decision-making in my line of work	Support of decision making
H2c	I believe I understand how AI systems work, in regards to underlying algorithms and data models that shape AI decisions and outputs.	Understanding of AI
H3	What is your Age, I have confidence in the output generated by AI systems for my line of work	Age & Score vs Confidence

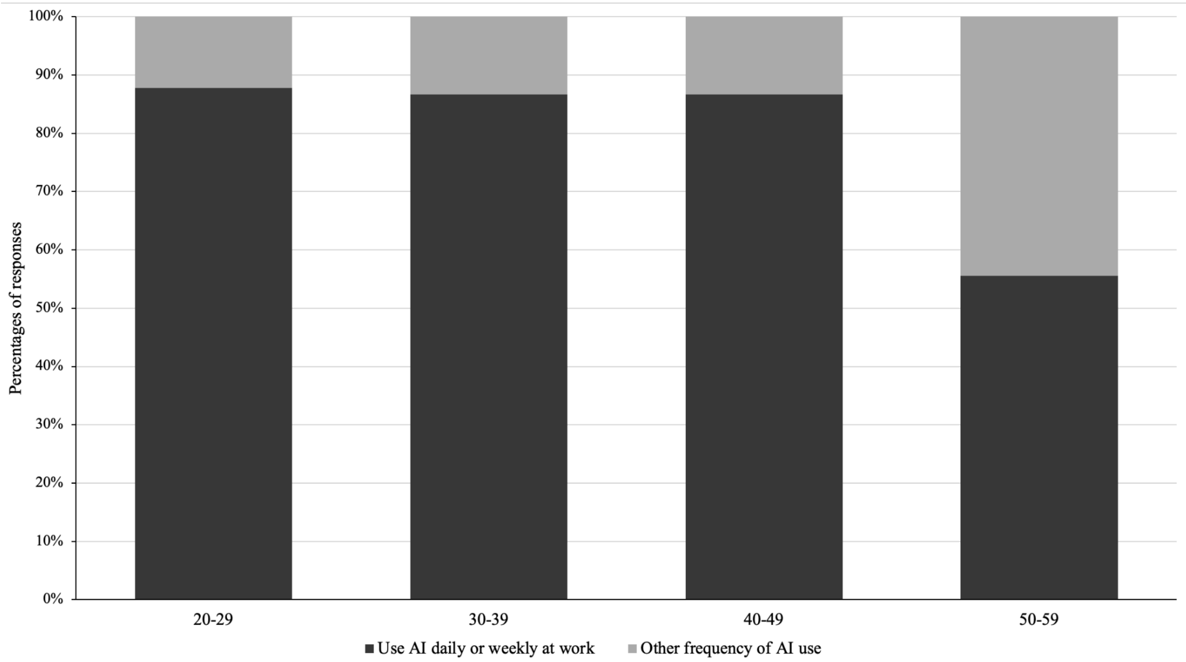
Table 1: Linkage between Hypothesis, Survey Questions & Category.

H1x		
Attitude Towards Using	**Subjective Norm**	**Perceived behavioural control**
I am of the opinion that the benefits of using AI in my line of work outweigh the downsides in my line of work.	My use of AI for work tasks is influenced by my peers or managers.	I feel that AI usage is easy to implement in my line of work
I find it necessary to use AI tools to keep up with my workload.	I worry that my use of AI may negatively influence how peers and managers perceive me.	
I believe that using AI increases the likelihood of incorrect or misleading information in my line of work.		
I feel it's necessary to stay up to date with AI technologies to remain competitive in today's job market.		

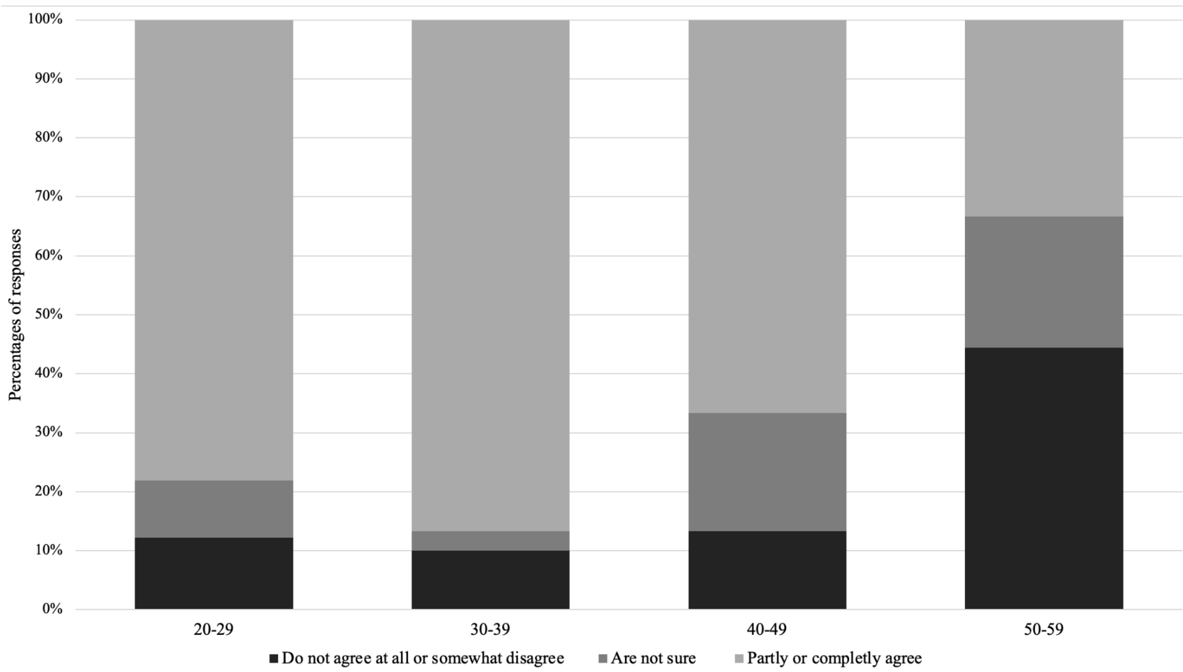
H2x & H3x	
Self literacy Score	**AI Literacy score**
I have sufficient skills and knowledge to increase efficiency in my line of work through the use of AI.	Which of the following terms best represent the technology that builds the core of a modern, intelligent AI system?
I rely on AI to support my decision-making in my line of work.	What are the purpose and objectives that AI is designed to achieve?
I believe I understand how AI systems work, in regards to underlying algorithms and data models that shape AI decisions and outputs.	How can AI perform the tasks it was designed to do?
I have confidence in the output generated by AI systems for my line of work.	In how AI performs tasks, which part of the process is directly connected to autonomous learning?

Table 3: Overview of survey questions linked to theoretical perspectives and hypotheses

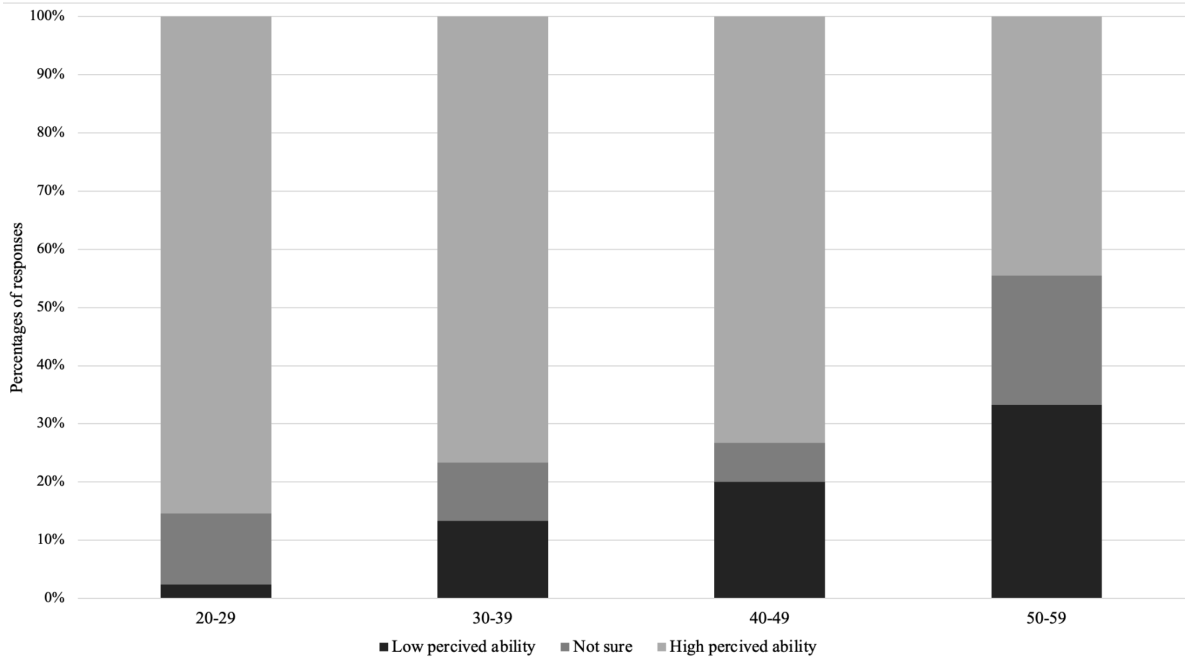
8.4 Analysis



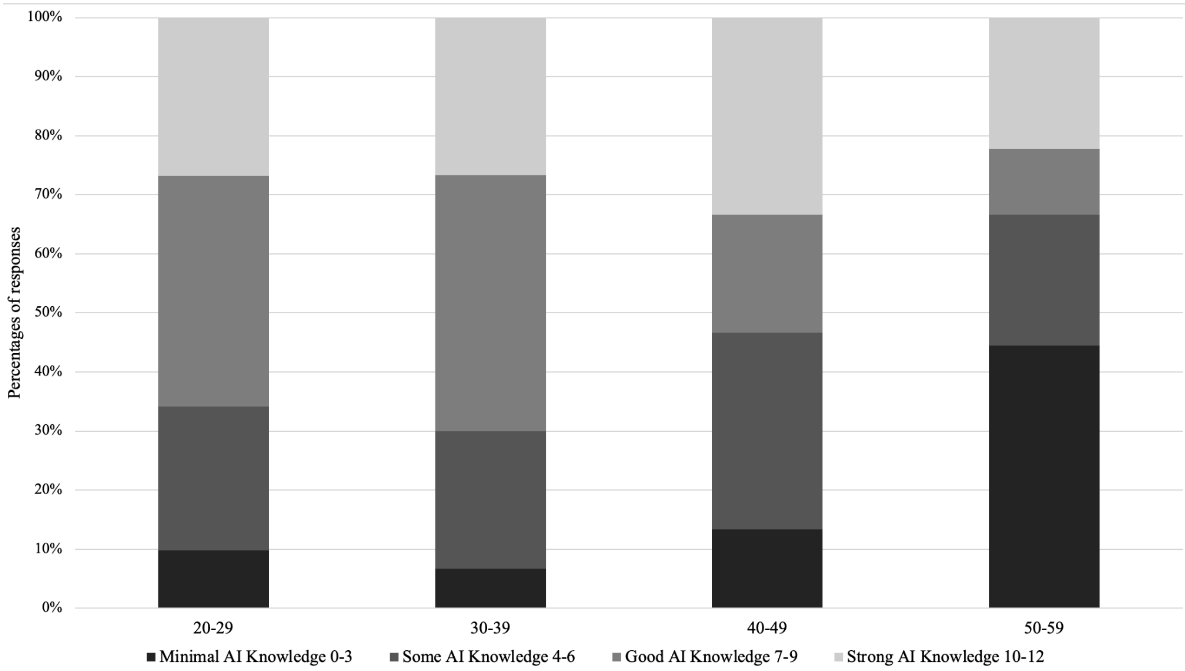
Graph 5.1.1 Frequent Vs infrequent AI usage at work across age groups



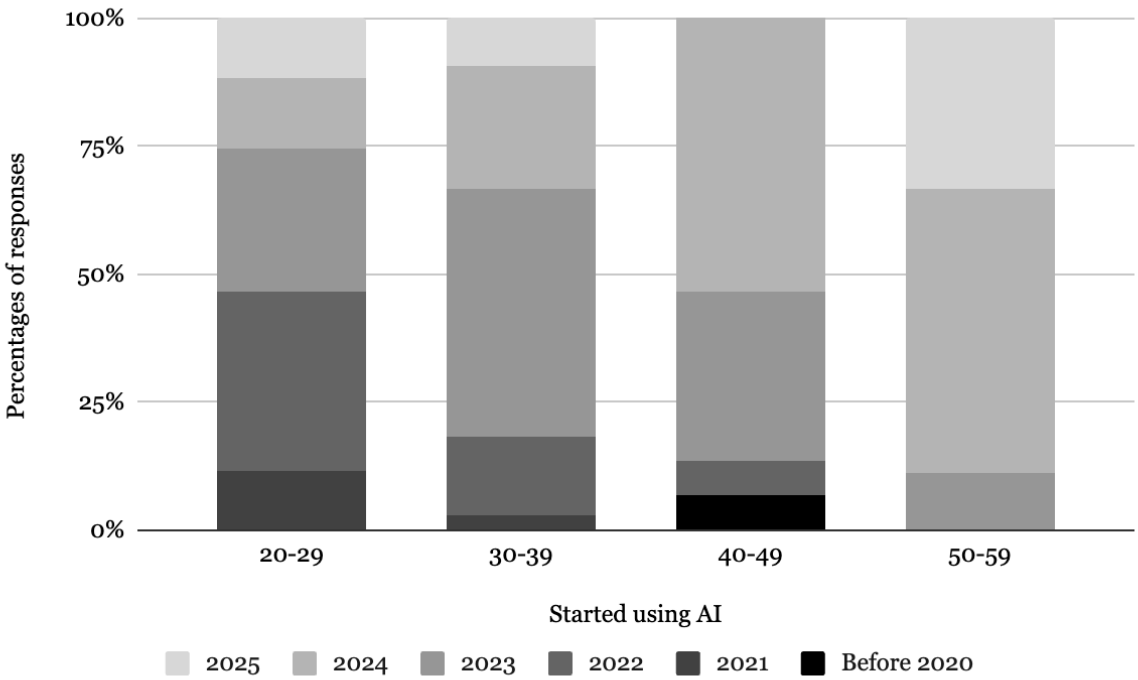
Graph 5.2.1 Confidence in AI-generated output across age groups



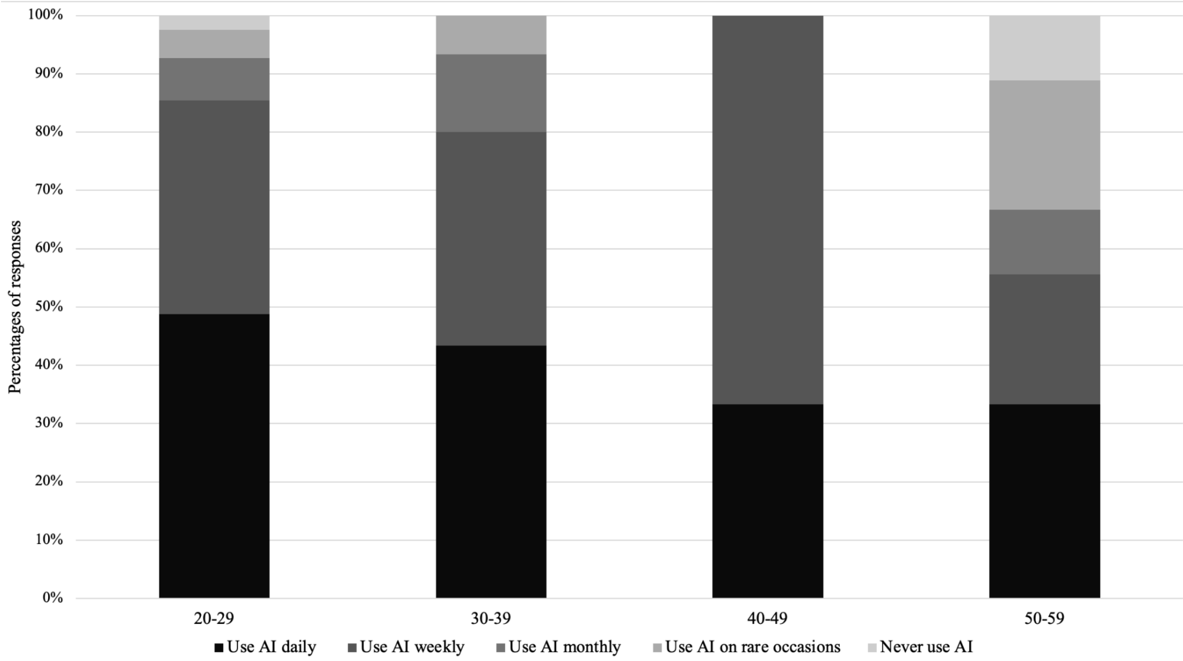
Graph 5.3.1 Perceived ability to use AI to enhance work efficiency by age group



Graph 5.4.1 AI literacy score



Graph 5.5.1 Year respondents started using AI by age group.



Graph 5.6.1 AI for personal use

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