“Hellenic Open University”

“Thesis for the MBA”

Postgraduate Dissertation

“Factors that influence the intention of using AI tools at work

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Patras, Greece, May 2026

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Abstract

The rapid development of artificial intelligence has transformed contemporary work practices, creating opportunities for productivity, decision support, automation and innovation. However, the adoption of AI tools in the workplace is associated not only with technological availability but also with employees' willingness to use them. The present cross-sectional study examines factors statistically associated with employees' intention to use AI tools at work, drawing mainly on the Theory of Planned Behavior. A quantitative research design was adopted, and data were collected through a structured questionnaire from 104 participants. Attitudes toward AI tools were the strongest statistical predictor of intention. Subjective norms were significant in the basic and extended regression models, but their direct effect was marginally non-significant in the final moderated model. Perceived behavioural control was significant in the basic TPB model but non-significant after previous AI experience was added. Previous AI experience and organisational innovation support, included as a contextual control variable, were positively associated with intention. The interaction between subjective norms and previous AI experience was negative and statistically significant, indicating that the association between subjective norms and intention was weaker at higher levels of AI experience. The findings should be interpreted as statistical associations rather than causal relationships. They highlight the relevance of attitudes, experience, organisational context and social cues in understanding employees' reported intention to use AI tools.

Keywords

artificial intelligence, AI tools, workplace adoption, intention to use, Theory of Planned Behavior.

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1 Chapter 1: Introduction

1.1 Background of the Study

Artificial intelligence has become one of the most influential technological developments in contemporary organisations. In recent years, AI tools have moved beyond specialised technical environments and have entered everyday work practices. Employees increasingly encounter AI through digital assistants, generative AI applications, automated recommendation systems, data analytics platforms, chatbots, translation tools, coding assistants and decision-support systems. These tools are now used across a wide range of work-related activities, including information search, document drafting, summarising, communication, data analysis, customer service, planning and problem-solving.

The increasing presence of AI in the workplace is part of a wider process of digital transformation. Organisations are not only adopting new technologies; they are also changing how tasks are performed, how decisions are supported and how employees interact with information. AI tools can improve productivity, reduce repetitive work, support creativity and assist employees in handling complex information. However, the adoption of AI also raises concerns related to trust, accuracy, transparency, ethics, privacy, professional autonomy and job security. Therefore, AI use in the workplace cannot be understood only as a technical issue. It is also a human, behavioural and organisational issue.

Although organisations may provide access to AI tools, actual adoption depends heavily on employees' willingness to use them. Employees may evaluate AI positively when they believe that it can help them work faster, improve the quality of their output or support decision-making. At the same time, they may hesitate if they do not trust AI-generated outputs, if they lack experience, if they are unsure about organisational rules, or if they fear that AI may reduce their professional value. For this reason, understanding the factors that influence employees' intention to use AI tools is important for both researchers and organisations.

The present study focuses on employees' intention to use AI tools at work. Intention is a key concept because it reflects employees' readiness and willingness to engage with AI in their professional tasks. The study is theoretically based on the Theory of Planned Behavior, according to which behavioural intention is influenced by attitudes toward the behaviour, subjective norms and perceived behavioural control (Ajzen, 1991). This framework is particularly suitable for the present topic because AI adoption depends on how employees evaluate AI tools, how they perceive social expectations around AI use and whether they feel capable of using such tools effectively.

In addition to the core elements of the Theory of Planned Behavior, the study also considers previous experience with AI tools and organisational innovation support. Previous AI experience is important because employees who have already used AI tools may have a clearer understanding of their usefulness, limitations and risks. Organisational innovation support is also relevant because AI adoption takes place within a workplace context. Employees may be more willing to use AI when their organisation encourages innovation, provides resources and supports learning.

Therefore, the present dissertation examines AI adoption from an employee-centred perspective. Rather than assuming that AI implementation automatically leads to use, it investigates the psychological and organisational factors that shape employees' intention. This approach is important because the success of AI in the workplace depends not only on the quality of the technology but also on whether employees are ready, willing and supported to use it responsibly.

1.2 Research Problem

The rapid development of AI tools has created new opportunities for organisations, but it has also created uncertainty about how employees respond to these technologies. Many organisations are interested in adopting AI because of its potential to improve efficiency, productivity and innovation. However, technological investment alone does not guarantee successful adoption. Employees may not use AI tools simply because they are available. Their intention to use AI depends on how they perceive the technology, how confident they feel, how their workplace environment supports them and how much previous experience they have.

A central problem is that AI adoption is often discussed mainly from a technological or organisational performance perspective, while employees' own perceptions may receive less attention. However, employees are the ones who are expected to integrate AI tools into everyday work routines. If they do not understand the value of AI, do not trust it, do not feel capable of using it or do not perceive social and organisational support, adoption may remain limited or superficial. In some cases, employees may avoid AI altogether. In other cases, they may use it informally without clear guidance, which can create risks related to data protection, accuracy and accountability.

Another issue is that employees may differ significantly in their responses to AI. Some may already have experience with AI tools and may feel comfortable using them. Others may have limited exposure and may rely more strongly on colleagues, supervisors or organisational messages when deciding whether AI use is appropriate. This creates a need to examine not only the direct predictors of AI adoption intention but also how previous experience may change the strength of these relationships.

The research problem of this dissertation is therefore the need to understand which factors influence employees' intention to use AI tools in the workplace. More specifically, the study investigates whether attitudes, subjective norms, perceived behavioural control and previous AI experience predict intention to use AI tools. It also examines whether previous AI experience moderates the relationship between subjective norms and intention. Organisational innovation support is considered as part of the broader context in which AI adoption takes place.

This research problem is important because organisations need evidence-based insights in order to design effective AI implementation strategies. If employees' intention is mainly shaped by attitudes, organisations should focus on demonstrating the practical value of AI. If subjective norms are important, managers and colleagues can play a role in normalising responsible AI use. If previous experience matters, organisations should provide hands-on training and safe opportunities for experimentation. Understanding these factors can help organisations promote AI adoption in a way that is not only efficient but also responsible and employee-centred.

1.3 Aim and Objectives of the Study

The main aim of this study is to examine the factors that influence employees' intention to use AI tools in the workplace. The study seeks to understand how employees' attitudes, perceived social expectations, perceived control, previous experience and organisational context are associated with their willingness to use AI tools for work-related purposes.

More specifically, the objectives of the study are:

1. To examine employees' attitudes toward the use of AI tools at work.
2. To investigate the relationship between subjective norms and employees' intention to use AI tools.
3. To examine whether perceived behavioural control predicts employees' intention to use AI tools.
4. To assess the contribution of previous AI experience to employees' intention to use AI tools.
5. To examine whether previous AI experience moderates the relationship between subjective norms and intention to use AI tools.
6. To consider the role of organisational innovation support as part of the broader context of workplace AI adoption.
7. To provide practical recommendations for organisations and managers regarding the responsible and effective adoption of AI tools in the workplace.

1.4 Structure of the Dissertation

The dissertation is organised into six chapters. Chapter 1 introduces the topic of the study. It presents the background of AI use in the workplace, defines the research problem, states the aim and objectives of the study and outlines the structure of the dissertation. Chapter 2 presents the literature review. It discusses artificial intelligence in the workplace, AI tools and the digital transformation of work, employees' intention to use AI tools and the theoretical background of the Theory of Planned Behavior. It also analyses the role of attitudes, subjective norms, perceived behavioural control, previous AI experience and organisational innovation support. The chapter concludes with a review of previous empirical studies and the development of the research model and hypotheses. Chapter 3 describes the methodology of the study. It explains the research design, research approach, population and sample, data collection procedure, research instrument and measurement of variables. It also presents the data analysis strategy, reliability and validity testing and ethical considerations. Chapter 4 presents the results of the empirical analysis. It includes descriptive statistics, reliability analysis, confirmatory factor analysis, Harman's one-factor test, correlation analysis, regression analysis and moderation analysis. The chapter reports the statistical findings and explains how they relate to the hypotheses of the study. Chapter 5 discusses the findings in relation to the research questions and previous literature. It interprets the role of attitudes, subjective norms, perceived behavioural control, previous AI experience, the moderating role of AI experience and organisational innovation support. It also presents the theoretical and practical implications of the study. Chapter 6 concludes the dissertation. It summarises the study, presents the main conclusions, provides recommendations for practice, identifies the limitations of the research and suggests directions for future studies.

2 Chapter 2: Literature Review

2.1 Artificial Intelligence in the Workplace

Artificial intelligence has become increasingly present in contemporary workplaces, not only as a specialised technological infrastructure but also as a set of tools that employees can use directly in their daily tasks. AI tools may include generative AI applications, chatbots, automated recommendation systems, data analytics platforms, translation tools, coding assistants and decision-support systems. These tools can support activities such as information search, writing, summarising, data interpretation, communication and problem-solving. Therefore, AI use in the workplace is not limited to technical departments or highly specialised users. It increasingly concerns ordinary employees who are expected to decide whether and how to integrate AI into their work routines.

For the purposes of the present study, AI tools are understood as digital applications that use artificial intelligence to generate, organise, analyse or recommend information in ways that can support work-related tasks. This understanding is consistent with the broader definition of AI as a machine-based system that can generate outputs such as predictions, recommendations, content or decisions from given inputs (OECD, 2024). In the workplace, such outputs may support employees by helping them complete tasks more efficiently or by assisting them in making better-informed decisions.

The adoption of AI tools at work, however, is not automatic. Even when organisations provide access to AI-based applications, employees may differ in their willingness to use them. Some may view AI as useful, time-saving and supportive of their work, while others may be sceptical because of concerns about accuracy, reliability, data privacy, professional responsibility or job security. This means that AI adoption should not be treated only as a technological issue. It is also a behavioural issue, because it depends on how employees evaluate AI tools and whether they feel willing and able to use them.

This employee-centred perspective is important because AI tools often require active judgement from users. Employees do not simply receive fixed outputs from AI systems. They need to decide when to use AI, how to formulate requests, how to interpret AI-generated results and whether those results are suitable for professional use. For example, a generative AI tool may help draft a report or summarise information, but the employee remains responsible for checking accuracy, adapting the output and ensuring that the final work meets professional standards. In this sense, the use of AI tools involves both technological interaction and personal responsibility.

Previous research suggests that employees' responses to AI are shaped by several psychological and organisational factors. Trust, perceived usefulness, perceived ease of use and affective attitudes are important in shaping employees' intention to use AI at work (Nguyen et al., 2026). Similarly, studies based on the Theory of Planned Behavior show that attitudes, subjective norms and perceived behavioural control can explain employees' intention to adopt AI in workplace contexts (Srivastava et al., 2024). These findings indicate that employees' willingness to use AI depends on whether they evaluate it positively, whether they perceive support from important others and whether they feel capable of using it effectively.

Attitudes are particularly important because employees are more likely to use AI tools when they believe that these tools are useful and beneficial for their work. If AI is perceived as helping employees save time, improve productivity or support decision-making, intention to use it is likely to increase. On the other hand, negative attitudes may emerge when AI is associated with errors, uncertainty, overreliance or loss of professional autonomy. For this reason, the present study examines attitudes toward AI tools as a key predictor of intention. Subjective norms are also relevant because workplace behaviour is socially embedded. Employees may be influenced by whether colleagues, supervisors or managers approve of AI use. In some workplaces, using AI may be seen as innovative and efficient. In others, employees may hesitate because AI use is unclear, discouraged or not yet normalised. Therefore, perceived social support may influence whether employees intend to adopt AI tools in their work.

Perceived behavioural control is another important factor. Employees may have positive views about AI but still avoid using it if they feel that they lack the necessary knowledge, skills, access or organisational permission. AI tools may appear easy to access, especially in the case of generative AI, but responsible use requires the ability to evaluate outputs, identify possible errors and protect sensitive information. Therefore, employees' perceived ability to use AI tools is central to adoption. Previous experience with AI tools may also shape intention. Employees who have already used AI may have a clearer understanding of its benefits and limitations. Experience can reduce uncertainty, increase confidence and make AI use feel more manageable. At the same time, previous experience may affect how strongly employees rely on social influence. Less experienced employees may depend more on the opinions of colleagues or supervisors, while more experienced employees may rely more on their own judgement.

2.2 AI Tools and Digital Transformation of Work

The use of AI tools is part of the wider digital transformation of work. Digital transformation refers to the integration of digital technologies into organisational processes, work practices and decision-making. However, in the present study, digital transformation is not examined as a broad organisational phenomenon. It is considered mainly as the context within which employees encounter AI tools and decide whether they intend to use them. This focus is important because the study does not aim to analyse digital transformation in general, but to understand the factors that influence employees' intention to use AI tools at work.

AI tools differ from many earlier digital technologies because they can generate content, support decisions, provide recommendations and interact with users through natural language. This makes them more visible and accessible to employees. For example, employees may use AI tools to draft text, summarise information, translate documents, analyse data or generate ideas. These uses may influence how employees perceive the usefulness of AI, how confident they feel in using it and whether they believe that AI can fit into their work routines.

In this context, digital transformation creates both opportunities and uncertainty. On the one hand, AI tools may help employees complete tasks more efficiently, reduce repetitive work and manage information overload. On the other hand, employees may be unsure about how reliable AI outputs are, whether AI use is acceptable within their organisation or whether they have the skills required to use such tools responsibly. Therefore, the digital transformation of work is directly connected with the variables examined in this study.

First, digital transformation may shape employees' attitudes toward AI tools. When AI is introduced as a practical tool that supports employees' actual tasks, employees may evaluate it more positively. If they experience AI as useful, relevant and compatible with their work, they are more likely to develop favourable attitudes. However, if AI is introduced without explanation or if it is perceived as a threat to professional autonomy, attitudes may become less favourable. This makes attitudes a central part of AI adoption.

Second, digital transformation can influence subjective norms. As AI tools become more common in organisations, employees may observe colleagues and managers using them. This can create a sense that AI use is normal, expected or professionally acceptable. In contrast, if AI use remains unclear or hidden, employees may hesitate. Social influence is therefore important because employees often look to their work environment to understand whether using a new technology is appropriate.

Third, digital transformation affects perceived behavioural control. Employees may intend to use AI tools only if they feel that they have the necessary skills, access and support. Training, clear guidelines, approved tools and technical assistance can increase perceived control. Without these conditions, employees may feel uncertain even if they are personally interested in AI. This is particularly relevant because AI tools require not only basic operation but also critical judgement, especially when outputs may be inaccurate or incomplete.

Fourth, digital transformation increases the importance of previous experience. Employees who have already used AI tools may be more familiar with how these tools work and where they can be useful. Such experience can make AI use less abstract and may increase intention. In contrast, employees with little experience may rely more on social cues from colleagues and supervisors. This is why previous AI experience is examined in the present study both as a direct predictor and as a moderator of the relationship between subjective norms and intention.

The literature on technology acceptance supports this focus. Earlier models, such as the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology, show that perceived usefulness, ease of use, social influence and facilitating conditions are important for technology adoption (Davis, 1989; Venkatesh et al., 2003). Although the present dissertation is based mainly on the Theory of Planned Behavior, these models reinforce the idea that technology adoption depends on employees' beliefs, perceptions and work conditions. In the case of AI tools, these factors are especially relevant because AI use involves both opportunity and uncertainty. Therefore, the role of AI tools in digital transformation should be linked directly to employees' intention to use them. The main issue is not only whether AI tools are available in organisations, but whether employees perceive them as useful, acceptable and controllable. This is why the present study focuses on attitudes, subjective norms, perceived behavioural control and previous experience. These variables make it possible to examine AI adoption from the perspective of employees rather than from a purely technological or managerial perspective.

2.3 Employees' Intention to Use AI Tools

Employees' intention to use AI tools is a central concept in understanding the successful integration of artificial intelligence into contemporary work. While organisations may invest in AI systems, provide access to digital platforms or encourage employees to experiment with new technologies, these actions do not automatically lead to meaningful use. The actual adoption of AI in daily work depends to a considerable extent on whether employees are willing to engage with these tools, trust their outputs and consider them relevant to their tasks. For this reason, behavioural intention is often treated as a key predictor of technology use in both technology acceptance research and behavioural theory (Ajzen, 1991; Davis, 1989; Venkatesh et al., 2003).

In the context of this dissertation, employees' intention to use AI tools refers to the degree to which employees are willing, prepared or motivated to use AI-based applications in their work-related activities. This may include the intention to use AI for information search, text generation, translation, data analysis, decision support, communication, content creation, administrative tasks or problem-solving. Intention does not necessarily mean that the employee is already using AI frequently. Rather, it reflects a psychological readiness to adopt or continue using AI tools when such use is available and relevant. This distinction is important because intention often precedes actual behaviour and can reveal the factors that make employees more or less likely to integrate AI into their work routines (Ajzen, 1991; Venkatesh et al., 2003).

The concept of intention is especially useful in the case of AI because AI adoption is not only a technical decision. It is also a personal and organisational decision shaped by perceptions, emotions, workplace norms, skills and trust. Employees may have access to the same AI tool but respond to it in very different ways. Some may see it as useful and time-saving, while others may experience uncertainty, fear of errors, concerns about confidentiality or anxiety about job replacement. Therefore, the study of intention helps explain why the availability of AI tools does not always translate into actual use. It also helps identify what organisations need to address if they want to promote responsible and effective AI adoption.

Technology acceptance research has long shown that intention is one of the strongest predictors of technology use. Davis (1989), through the Technology Acceptance Model, argued that perceived usefulness and perceived ease of use influence users' attitudes and behavioural intention toward information systems. Later, Venkatesh et al. (2003) proposed the Unified Theory of Acceptance and Use of Technology, where behavioural intention is influenced by performance expectancy, effort expectancy and social influence. Although these models were not originally developed for AI, they remain relevant because AI tools are also technologies that employees evaluate in terms of usefulness, effort, social expectations and facilitating conditions. In AI-specific research, these factors are often combined with additional constructs such as trust, perceived risk, AI anxiety, transparency and ethical concern (Glikson & Woolley, 2020; Nguyen et al., 2026).

Recent empirical studies confirm that employees' intention to use AI at work is influenced by both cognitive and affective evaluations. Nguyen et al. (2026) examined employees' perceptions of AI in the workplace using data from 1,224 working adults across two samples. Their study found that trust in AI, perceived usefulness and perceived ease of use shape affective attitudes toward using AI, which in turn influence employees' intentions to adopt AI in their job. This finding is important because it shows that intention is not based only on rational calculations of efficiency. It is also shaped by how employees feel about AI. If employees associate AI with confidence, curiosity and professional benefit, they may be more willing to use it. If they associate it with distrust, uncertainty or discomfort, their intention may be weaker.

The role of trust is particularly important in AI adoption. Unlike many traditional digital tools, AI systems often produce outputs that are probabilistic, complex or difficult for non-specialist users to fully understand. Employees may not always know how an AI tool produced a recommendation, summary or prediction. As a result, they must decide whether the tool is reliable enough to be used in professional tasks. Glikson and Woolley (2020) argue that trust in AI depends on factors such as transparency, reliability, task context and the form in which AI is presented. In the workplace, trust may be even more important because employees remain accountable for the outcomes of their work. An employee may use AI to support a decision, but responsibility for checking the output and applying it appropriately usually remains with the human user.

Employees' intention to use AI tools is also closely connected to perceived usefulness. If employees believe that AI can improve their performance, save time, reduce workload or support better decision-making, their intention to use it is likely to increase. This is consistent with the Technology Acceptance Model, where perceived usefulness is one of the strongest predictors of behavioural intention (Davis, 1989). In the case of AI, usefulness may take several forms. It may refer to faster completion of routine tasks, improved access to information, support for creativity, enhanced accuracy or better organisation of work. However, perceived usefulness is not objective. It depends on whether employees can clearly see how AI fits their own job tasks. A tool that is useful for one role may appear irrelevant or difficult to apply in another.

At the same time, intention to use AI is shaped by perceived effort and complexity. Employees are more likely to intend to use AI tools when they believe they can learn and operate them without excessive difficulty. This is especially relevant for employees who have limited previous experience with AI or who feel less confident with digital technologies. Although many generative AI tools are designed to be easy to use, effective use still requires judgement, experimentation and critical evaluation. Employees need to know how to ask appropriate questions, interpret the outputs, detect possible errors and decide whether the result is suitable for professional use. Therefore, ease of use in AI adoption is not only about the interface. It is also about whether employees feel capable of using the tool responsibly.

Another important factor is perceived behavioural control, which refers to the extent to which individuals believe they have the ability, resources and opportunities to perform a behaviour (Ajzen, 1991). In the context of AI tools, employees may intend to use AI when they believe they have sufficient knowledge, access, time, training and organisational permission. If these conditions are absent, intention may be limited even when attitudes are positive. For example, an employee may believe that AI could be useful but may avoid using it because the organisation has not provided clear guidelines or because the employee is uncertain about data protection rules. This shows that intention is not simply a matter of personal preference. It is also shaped by the practical and organisational conditions surrounding AI use.

Subjective norms also influence employees' intention to use AI tools. In workplace settings, employees are sensitive to what colleagues, supervisors, managers and professional communities consider acceptable or desirable. If important others encourage AI use, discuss it positively or incorporate it into normal work practices, employees may feel stronger social pressure or motivation to adopt it. Conversely, if AI use is viewed with suspicion or if employees fear that using AI may be judged negatively, they may hesitate. Srivastava et al. (2024), in a study of employees in the United Arab Emirates, applied the Theory of Planned Behavior to AI adoption at work and found that attitude, subjective norms and perceived behavioural control all had significant effects on employees' intention to use AI. The study also reported a positive relationship between intention and behaviour among employees using AI at work.

The relationship between intention and actual use, however, should not be treated as automatic. Behavioural intention is a strong predictor of behaviour, but actual use can be constrained by external conditions. Employees may intend to use AI but lack access to approved tools, adequate training or managerial permission. They may also face organisational restrictions due to confidentiality, legal compliance or ethical concerns. On the other hand, some employees may use AI even when organisational policies are unclear, especially if they believe the tool helps them complete tasks faster. This means that intention must be understood within the broader context of organisational governance, digital infrastructure and workplace culture.

Recent research on generative AI in work settings also supports the importance of organisational conditions. Samudra et al. (2024) examined the intention to use generative AI in the workplace using the UTAUT framework and data from office workers in Indonesia. Their findings indicated that performance expectations and facilitating conditions significantly influenced behavioural intention to adopt generative AI, while ease of use and social influence had more limited effects in that context. This finding is useful because it suggests that employees may be particularly motivated to use AI when they see clear performance benefits and when the organisation provides the necessary infrastructure and support.

Employees' intention to use AI tools is also affected by emotional responses. AI may create enthusiasm because it promises productivity, creativity and professional growth. At the same time, it may create anxiety because employees may worry about making mistakes, being replaced, losing control or being monitored. Chang et al. (2024) examined AI-driven technostress and found that challenge technology stressors can increase AI adoption intention through positive affect, while hindrance technology stressors can reduce adoption intention through AI anxiety. Their study also showed that technical self-efficacy plays a moderating role, meaning that employees who feel more capable of dealing with technology are better able to respond positively to AI-related demands.

2.4 Theoretical Background: The Theory of Planned Behavior

The present study is theoretically grounded in the Theory of Planned Behavior (TPB), one of the most widely used frameworks for explaining and predicting human behaviour in contexts where individuals make deliberate choices. The TPB was developed by Ajzen (1991) as an extension of the Theory of Reasoned Action, with the aim of explaining behaviours that are not fully under a person's voluntary control. Its central assumption is that behaviour is immediately preceded by behavioural intention, which reflects an individual's motivation, willingness, or readiness to perform a specific behaviour. In other words, the stronger a person's intention to perform a behaviour, the more likely it is that the behaviour will occur, provided that the individual also has sufficient actual control over the action (Ajzen, 1991, 2020).

The TPB is particularly suitable for studying employees' intention to use AI tools because workplace AI adoption is usually not an automatic reaction to technological availability. Employees often need to decide whether they will integrate AI tools into their tasks, whether they trust them enough to use them, whether they feel capable of using them appropriately, and whether their work environment supports such use. Therefore, the decision to use AI is not only technical, but also psychological and social. This makes the TPB a useful theoretical lens, as it explains behavioural intention through three major determinants: attitude toward the behaviour, subjective norms, and perceived behavioural control (Ajzen, 1991). These three constructs are also directly aligned with the main variables examined in the present dissertation.

According to Ajzen (1991), attitude toward the behaviour refers to the degree to which an individual evaluates a behaviour positively or negatively. In the context of AI tools at work, attitude concerns whether employees believe that using AI is beneficial, useful, efficient, interesting, risky, unnecessary, or problematic. Attitudes are formed through behavioural beliefs, meaning beliefs about the likely outcomes of the behaviour and the evaluation of those outcomes (Ajzen, 1991). For example, an employee may believe that AI tools can save time, improve productivity and support decision-making. If these outcomes are evaluated positively, the employee is likely to develop a favourable attitude toward AI use. Conversely, if the employee believes that AI tools may produce errors, reduce professional autonomy or create ethical risks, the attitude may become less favourable.

The second determinant of intention is subjective norms, which refer to perceived social pressure to perform or not perform a behaviour (Ajzen, 1991). Subjective norms are based on normative beliefs about whether important others approve of the behaviour and whether the individual is motivated to comply with these expectations. In a workplace setting, important others may include supervisors, colleagues, managers, clients, professional networks or the wider organisational culture. In relation to AI tools, employees may be more likely to intend to use AI when they believe that their colleagues use it, that their supervisors encourage it, or that the organisation views AI use as a legitimate and desirable practice. By contrast, if employees believe that AI use is discouraged, stigmatised or associated with unprofessional behaviour, their intention to use such tools may be weakened.

The third determinant is perceived behavioural control, which refers to the perceived ease or difficulty of performing the behaviour (Ajzen, 1991). This construct was the main addition of the TPB compared with the earlier Theory of Reasoned Action, because it recognises that behaviour is often constrained by available resources, skills, opportunities and barriers. In the context of AI tools, perceived behavioural control refers to whether employees believe that they have the knowledge, confidence, access, time, training and organisational permission required to use AI effectively. Even if employees hold positive attitudes toward AI and perceive social support for its use, they may still have weak intention if they feel that they lack the ability or resources to use AI tools properly.

A major strength of the TPB is that it does not assume that intention is shaped by only one type of factor. Instead, it combines personal evaluation, social influence and perceived control within a single explanatory model. This is valuable for the present research because employees' intention to use AI tools is likely to be shaped by multiple dimensions at the same time. Some employees may intend to use AI because they personally find it useful. Others may be influenced by the expectations of their organisation or colleagues. Others may base their intention mainly on whether they feel capable of using AI without making mistakes. The TPB allows all these pathways to be examined in a coherent and theoretically grounded way.

The relationship between intention and behaviour is also important. In the TPB, intention is considered the most immediate predictor of behaviour, but the strength of this relationship depends on actual behavioural control (Ajzen, 1991, 2020). This means that an employee may intend to use AI tools but may not actually use them if the organisation does not provide access, if the tools are blocked, if there are no clear policies, or if the employee does not have enough time or training. Similarly, an employee may have moderate intention but use AI frequently because the organisation requires it or integrates it into everyday systems. Therefore, intention is a necessary but not always sufficient condition for actual behaviour. This distinction is important in workplace AI research because the use of AI depends both on individual motivation and on organisational conditions.

The TPB has been applied across many research areas, including health behaviour, consumer behaviour, environmental behaviour, education, technology use and organisational behaviour. Meta-analytic evidence has generally supported the predictive value of the theory. Armitage and Conner (2001), in a meta-analytic review, found that the TPB accounted for substantial variance in both intention and behaviour across different domains. Similarly, McEachan et al. (2011) confirmed the usefulness of the TPB in predicting health-related behaviours, while also showing that the strength of the model may vary depending on the type of behaviour and measurement approach. Although these studies are not focused on AI, they support the broader validity of the TPB as a framework for studying intentional behaviour.

At the same time, the TPB has also been discussed critically. One common criticism is that intention does not always translate into behaviour, a problem often described as the intention–behaviour gap (Sheeran, 2002). This gap occurs when individuals form an intention but fail to act on it because of habits, environmental barriers, lack of resources, competing demands or changes in circumstances. In the case of AI use at work, this gap may occur when employees are willing to use AI but do not know which tools are approved, lack training, fear breaching confidentiality rules or feel that using AI would not be accepted in their department. Therefore, the TPB is useful not because it explains everything, but because it identifies the main motivational conditions that make behaviour more or less likely.

Another criticism is that the original TPB may not fully capture emotional, moral or identity-related influences on behaviour. Conner and Armitage (1998) argued that additional variables, such as moral norms, self-identity, anticipated regret and past behaviour, can sometimes improve the explanatory power of the model. This is relevant to AI adoption because employees' responses to AI may involve emotions such as curiosity, anxiety, fear, enthusiasm or distrust. They may also involve professional identity, especially when AI tools appear to perform tasks that employees consider part of their expertise. However, these limitations do not reduce the value of the TPB for the present study. Instead, they suggest that the basic TPB model may be enriched by considering variables such as previous AI experience and organisational innovation support.

The role of previous experience is particularly important. Although past behaviour is not one of the three original TPB predictors, it has often been examined in extended TPB models because previous experience can shape attitudes, perceived control and intention (Conner & Armitage, 1998; Ajzen, 2020). In the context of AI tools, employees who have already used AI may have more concrete beliefs about its usefulness, limitations and risks. Their attitudes may therefore be based on direct experience rather than abstract expectations. Previous experience may also increase perceived behavioural control, because employees who have used AI tools before may feel more confident about using them again. For this reason, including AI experience in the research model is theoretically justified.

The TPB is also closely related to technology adoption research. Although models such as the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology use different terminology, they share important similarities with the TPB. For example, perceived usefulness is conceptually related to positive behavioural beliefs and attitudes, while effort expectancy and facilitating conditions are related to perceived behavioural control (Davis, 1989; Venkatesh et al., 2003). Social influence in technology acceptance models is also closely connected to subjective norms. Therefore, the TPB provides a strong behavioural foundation for examining technology adoption while allowing the present study to focus specifically on intention, attitudes, social norms and perceived control.

Recent AI-related studies have also used the TPB to explain adoption intentions. Ivanov et al. (2024) applied the TPB to generative AI adoption in higher education and examined how perceived benefits, strengths, weaknesses and risks are associated with attitude, subjective norms, perceived behavioural control, intention and actual use. Their study is important because it shows that the TPB can be adapted to the specific case of generative AI, where both opportunities and risks shape users' behavioural intentions. Similarly, Srivastava et al. (2024) used the TPB to study AI adoption in the workplace and found that attitude, subjective norms and perceived behavioural control significantly influenced employees' intention to use AI at work. These findings support the relevance of the TPB for the present dissertation, which also examines employees' intention to use AI tools in a workplace context.

2.5 Attitudes toward the Use of AI Tools

Attitudes toward the use of AI tools constitute one of the most important psychological factors in explaining whether employees intend to adopt artificial intelligence in their work. Within the Theory of Planned Behavior, attitude refers to the degree to which a person evaluates a specific behaviour positively or negatively (Ajzen, 1991). In the present context, this means that employees are more likely to intend to use AI tools when they believe that using them at work is useful, beneficial, efficient, appropriate, and personally or professionally valuable. By contrast, negative attitudes may emerge when employees associate AI tools with risks, uncertainty, job insecurity, loss of autonomy, ethical concerns, or poor reliability.

Attitudes are especially important in AI adoption because AI tools are not neutral from the employee's perspective. They are often connected with expectations about productivity, competence, professional identity, trust, and future employability. An employee does not simply decide whether to use a technical system. Instead, the employee evaluates what AI use means for the quality of work, the speed of task completion, the level of responsibility, and the employee's own role within the organisation. This makes attitude a broader evaluative construct that includes both instrumental beliefs, such as usefulness and efficiency, and affective reactions, such as interest, confidence, anxiety, or discomfort (Ajzen, 1991; Glikson & Woolley, 2020).

In technology acceptance research, attitudes have long been recognised as a central element of adoption. Davis (1989) argued that users' acceptance of information technology depends strongly on perceived usefulness and perceived ease of use. These beliefs influence attitudes toward using the system and, in turn, shape behavioural intention. Although AI tools are more complex than many earlier information systems, the basic logic remains relevant. Employees are more likely to form favourable attitudes toward AI when they believe that AI tools improve their performance, reduce effort, support decision-making, and fit their work needs. Recent AI-specific research also supports this view. Nguyen et al. (2026) found that trust in AI and perceived usefulness are associated with employees' affective attitudes toward AI use at work, which subsequently influence intentions to adopt AI in their job.

A positive attitude toward AI tools may be formed when employees experience AI as a practical support mechanism. For example, AI may help employees summarise long documents, draft written material, generate ideas, organise information, translate texts, analyse data, or prepare reports. These functions can reduce cognitive burden and make work more efficient. When employees perceive such benefits, AI may be evaluated as a useful assistant rather than as a threat. This positive evaluation is important because attitudes are often based on expected outcomes. If employees believe that AI use will lead to better performance, time savings, improved creativity, or reduced routine work, their attitude is likely to become more favourable (Davis, 1989; Venkatesh et al., 2003).

However, attitudes toward AI tools are not shaped only by perceived benefits. They are also influenced by perceived risks. Unlike traditional software, AI systems may generate outputs that are difficult to fully explain, may contain errors, or may reproduce bias. Employees may therefore hesitate to evaluate AI positively if they believe that the tools are unreliable or risky. Glikson and Woolley (2020) emphasise that trust in AI depends on issues such as transparency, reliability, task characteristics, and the way AI is presented to users. When trust is low, employees may form negative attitudes even if the tool appears technically advanced. In workplace settings, this is particularly important because employees remain responsible for the quality and consequences of their work. Another source of negative attitude is fear of job displacement. Employees may perceive AI tools as technologies that could reduce the need for human labour or weaken the value of professional expertise. Even when AI is introduced as a supportive tool, employees may worry that its long-term purpose is cost reduction, monitoring, or replacement. Research on AI in organisations shows that AI can create both opportunities and anxieties for workers, particularly because it may alter task structures, professional identity, and perceived job security (Bankins et al., 2024). Therefore, an employee's attitude toward AI use may depend on whether the technology is framed as augmentation or substitution. When AI is presented as a tool that supports human expertise, attitudes may be more favourable. When it is perceived as a mechanism of replacement or control, attitudes may become more resistant.

The distinction between cognitive and affective attitudes is useful here. Cognitive attitudes are based on beliefs about the consequences of using AI, such as whether it is useful, accurate, efficient, or easy to integrate into work. Affective attitudes refer to feelings associated with AI use, such as enjoyment, curiosity, fear, anxiety, or discomfort. Both dimensions can influence intention. For example, an employee may cognitively recognise that AI can save time but still feel uncomfortable using it because of concerns about errors or ethical responsibility. Conversely, another employee may feel curious and motivated to experiment with AI even before having a full understanding of its technical limitations. Nguyen et al. (2026) specifically highlight the importance of affective attitudes in workplace AI adoption, showing that employees' perceptions of AI shape emotional evaluations, which then affect intention to use AI at work.

Attitudes toward AI are also shaped by previous experience. Employees who have already used AI tools may develop more concrete and stable attitudes than those who have only heard about AI through media, colleagues, or organisational communication. Positive experience can strengthen favourable attitudes because employees see directly how AI can support their work. For instance, if an employee uses an AI tool to complete a task more quickly or to improve the quality of a document, the employee may become more open to future use. Negative experience, however, can weaken attitude. If AI produces inaccurate information, irrelevant suggestions, or outputs that require excessive correction, employees may begin to view it as unreliable or inefficient. In this sense, attitudes toward AI are not fixed; they are formed and revised through interaction with the technology.

The role of experience is particularly relevant for generative AI tools. These tools often provide immediate and visible outputs, which can quickly shape users' impressions. A good response may create enthusiasm, while a poor response may create distrust. Because generative AI outputs can appear fluent even when they are inaccurate, employees may also develop ambivalent attitudes. They may appreciate the speed and convenience of the tool but remain cautious about relying on it. This ambivalence is important because attitudes toward AI are not always purely positive or negative. Employees may simultaneously recognise the usefulness of AI and worry about its limitations. Daly (2025), in qualitative research on organisational AI adoption, identifies positive, negative, and instrumental attitudinal positions toward AI, suggesting that employees' attitudes may be dynamic rather than stable or one-dimensional.

Workplace attitudes toward AI are also influenced by organisational communication. When management explains why AI tools are introduced, how they should be used, and what protections are in place, employees may develop more positive attitudes. Clear communication can reduce uncertainty and help employees understand the purpose of AI adoption. In contrast, if AI is introduced without explanation, employees may fill the gap with assumptions. They may suspect that the technology is intended to monitor performance, reduce staff, or intensify work. This can lead to negative attitudes even before employees have direct experience with the tool. Bankins et al. (2024) argue that AI has multilevel implications for organisations, meaning that employee perceptions are shaped not only by the tool itself but also by organisational practices, leadership, and work design.

Training also plays a significant role in attitude formation. Employees who receive AI-related training are more likely to understand the potential and limitations of AI tools. Training can reduce fear, improve confidence, and help employees evaluate AI outputs critically. This is important because negative attitudes may sometimes come from uncertainty rather than direct opposition. If employees do not understand how AI works, what it can do, or how it should be used safely, they may avoid it. Training can therefore improve attitudes by increasing familiarity and reducing perceived complexity. Babashahi et al. (2024) argue that AI in the workplace is associated with skill transformation, as employees increasingly need to combine domain knowledge with AI-related and digital skills. This means that attitudes toward AI may improve when employees feel that they are being supported in developing the skills required for responsible use.

Another important factor is perceived ethicality. Employees may evaluate AI negatively if they believe that its use violates fairness, privacy, transparency, or professional standards. For example, AI tools used in recruitment, performance evaluation, or customer profiling may raise concerns about bias and accountability. Even when employees personally find AI useful, they may hesitate if they believe that its use could harm others or produce unfair outcomes. The NIST AI Risk Management Framework stresses that trustworthy AI requires attention to validity, reliability, safety, accountability, transparency, explainability, privacy, and fairness (NIST, 2023). These dimensions are relevant to attitudes because employees' evaluations of AI are likely to become more favourable when they perceive AI use as responsible and well-governed.

Attitudes toward AI tools may also vary depending on the type of task. Employees may have positive attitudes toward AI for low-risk or supportive tasks, such as summarising notes, drafting routine emails, or organising information. However, they may be less positive toward AI use in high-stakes decisions, such as hiring, medical diagnosis, legal judgement, or performance evaluation. This is consistent with trust research, which suggests that people evaluate AI differently depending on the task and the level of risk involved (Glikson & Woolley, 2020). Therefore, attitude toward AI use should not be interpreted as a general opinion about all AI technologies. In empirical research, it is important to define the behaviour clearly, such as using AI tools for work-related tasks.

The relation between attitude and intention has been supported in AI adoption studies. Srivastava et al. (2024), applying the Theory of Planned Behavior to workplace AI adoption, reported that attitude, subjective norms, and perceived behavioural control significantly influence employees' intention to use AI at work. Their findings are directly relevant to the present dissertation because they confirm that the TPB can be applied to employees' AI adoption intention in organisational settings. Similarly, Ivanov et al. (2024)

found that attitudes are part of the mechanism through which perceived benefits, strengths, weaknesses, and risks of generative AI influence intention and actual use in a higher education context. Although their study is not focused on workplace employees, it is relevant because it demonstrates how attitudes toward generative AI are shaped by both positive and negative evaluations.

Attitudes toward AI may also interact with perceived usefulness and trust. In many cases, employees may first evaluate whether the tool is useful, then decide whether they feel positively toward using it. If AI is perceived as useful but untrustworthy, attitudes may remain mixed. For example, an employee may believe that AI can save time but may not trust the accuracy of its outputs. Conversely, if AI is both useful and trusted, the employee's attitude is likely to be more favourable. Nguyen et al. (2026) found that trust and perceived usefulness were important in shaping affective attitudes toward workplace AI, which then influenced intention. This suggests that attitudes operate as a bridge between specific beliefs about AI and behavioural intention.

The emotional side of attitude becomes even more important when AI is associated with technostress. Chang et al. (2024) examined whether AI-driven technostress promotes or hinders employees' AI adoption intention. Their findings suggest that challenge-related technology stressors can increase positive affect and support adoption intention, while hindrance-related stressors can trigger AI anxiety and reduce adoption intention. This shows that employee attitudes may depend on whether AI is experienced as a manageable challenge or as an overwhelming burden. For organisations, this means that the goal is not to remove all difficulty from AI adoption, but to ensure that employees perceive learning AI as achievable and meaningful.

2.6 Subjective Norms and Social Influence in AI Adoption

Subjective norms constitute the second core predictor of behavioural intention in the Theory of Planned Behavior. While attitudes refer to the employee's personal evaluation of using AI tools, subjective norms refer to the perceived social expectations surrounding this behaviour. According to Ajzen (1991), subjective norms describe the extent to which individuals believe that important others think they should or should not perform a specific behaviour. In the workplace, this means that employees' intention to use AI tools may be shaped not only by what they personally think about AI, but also by what they believe their colleagues, supervisors, managers, professional peers, or wider organisational environment expect from them.

In the TPB, subjective norms are based on normative beliefs. These beliefs concern whether important referent individuals or groups approve of the behaviour, combined with the individual's motivation to comply with those expectations (Ajzen, 1991). In the case of AI tools, relevant referents may include line managers, senior leadership, team members, IT departments, clients, professional associations and even informal peer groups. For example, if an employee believes that their supervisor expects them to use AI to improve productivity, and if the employee values the supervisor's opinion, subjective norms may positively influence intention. Similarly, if colleagues regularly use AI tools and describe them as helpful, the employee may interpret AI use as part of normal workplace behaviour.

The influence of subjective norms is closely connected to broader theories of social influence. Cialdini and Goldstein (2004) explain that people often adjust their behaviour in response to social expectations, group norms and the desire for social approval. This does not mean that employees simply imitate others. Rather, social influence can operate through several mechanisms, including conformity, identification, internalisation and informational influence. In uncertain situations, individuals often look to others to decide what behaviour is appropriate. AI adoption creates exactly this kind of uncertainty for many employees. Because AI tools are relatively new, complex and sometimes controversial, employees may use the behaviour of colleagues and managers as cues for whether AI use is acceptable, safe and professionally appropriate.

A useful distinction can be made between injunctive and descriptive norms. Injunctive norms refer to what people believe others approve or disapprove of, while descriptive norms refer to what people believe others are actually doing (Cialdini et al., 1990). Both forms are relevant to AI adoption. An injunctive norm may exist when managers explicitly state that employees should use approved AI tools responsibly. A descriptive norm may exist when employees observe that many colleagues already use AI for writing, summarising, coding, analysis or administrative tasks. These two forms of social influence may reinforce each other, but they may also diverge. For instance, an organisation may formally encourage innovation, but employees may notice that few colleagues actually use AI. In this case, the descriptive norm may weaken the effect of managerial encouragement. Alternatively, employees may observe widespread informal AI use even in the absence of clear official policies, which may create a descriptive norm but also uncertainty about whether the practice is fully approved.

Social influence has also been recognised as an important factor in technology adoption models. In the Unified Theory of Acceptance and Use of Technology, social influence refers to the extent to which individuals perceive that important others believe they should use a new system (Venkatesh et al., 2003). This construct is conceptually close to subjective norms and has been shown to influence behavioural intention, especially when technology use is new, visible or organisationally encouraged. Venkatesh and Davis (2000) also argued that social influence processes can affect technology acceptance through subjective norms, image and perceived usefulness. In organisational contexts, employees may adopt technology partly because it signals competence, adaptability or alignment with organisational expectations. This logic is highly relevant to AI tools, which are often associated with innovation, digital readiness and future-oriented work practices.

Meta-analytic evidence from technology acceptance research confirms that subjective norms and social influence can play a meaningful role in technology adoption. Schepers and Wetzels (2007), in a meta-analysis of the Technology Acceptance Model, found that subjective norms are related to perceived usefulness and behavioural intention. This suggests that social expectations may influence adoption both directly and indirectly. Employees may not only feel pressure to use a technology but may also come to perceive it as more useful when respected colleagues or managers endorse it. In the case of AI tools, this may occur when supervisors communicate practical examples of AI benefits, when expert users demonstrate successful use, or when teams collectively integrate AI into shared workflows.

Recent empirical research supports the relevance of subjective norms in AI adoption. Srivastava et al. (2024) applied the Theory of Planned Behavior to employees' AI adoption in the workplace and found that attitude, subjective norms and perceived behavioural control all had a significant effect on intention to use AI at work. This finding is directly relevant to the present study because it confirms that employees' AI adoption intention is shaped not only by individual evaluations but also by perceived social expectations in the workplace.

Evidence from generative AI research also points in the same direction. Ivanov et al. (2024), using the TPB to examine generative AI adoption in higher education, found that TPB variables, including subjective norms, are relevant for explaining intention to use generative AI tools. Although the study was conducted in an educational rather than an employee workplace context, it is still useful because generative AI adoption involves similar questions about legitimacy, perceived usefulness, risk and social approval. In addition, Nguyen et al. (2026) showed that employees' perceptions and affective attitudes influence intentions to use AI at work, which complements the TPB perspective by showing that social and psychological evaluations are part of the adoption process.

Another important aspect is the visibility of AI use. Social influence tends to be stronger when the behaviour is visible to others (Venkatesh et al., 2003). Some forms of AI use are visible, such as using AI-generated slides in a meeting or discussing AI-supported analysis with colleagues. Other forms are private, such as using a chatbot to draft an email or summarise a document. When AI use is private, subjective norms may still matter, but employees may have more freedom to experiment without direct social judgement. When AI use is visible, employees may be more sensitive to how others evaluate it. This can either encourage use, when AI is socially approved, or discourage use, when employees fear criticism.

Social influence may also contribute to the diffusion of AI tools across organisations. Innovation diffusion theory suggests that new technologies spread through communication channels, social systems and perceived characteristics of the innovation (Rogers, 2003). Early adopters can influence others by demonstrating practical value and reducing uncertainty. In AI adoption, employees who experiment successfully with AI may become informal champions. Their behaviour can create positive descriptive norms and encourage wider adoption. However, diffusion may be uneven if AI use remains limited to technologically confident employees or specific departments. Organisations that want broader AI adoption need to support not only individual users but also shared learning across teams.

2.7 Perceived Behavioural Control and AI Use

Perceived behavioural control is the third central determinant of intention in the Theory of Planned Behavior and refers to the extent to which individuals believe that they are capable of performing a specific behaviour and that the necessary resources and opportunities are available to them (Ajzen, 1991). In contrast to attitudes, which concern whether the behaviour is evaluated positively or negatively, and subjective norms, which concern perceived social expectations, perceived behavioural control focuses on the employee's sense of capability and control. In the context of AI tools at work, it reflects whether employees believe they have the knowledge, skills, access, time, organisational permission and confidence required to use AI effectively.

Ajzen (1991) introduced perceived behavioural control into the Theory of Planned Behavior because many behaviours are not completely under voluntary control. A person may have a positive attitude and perceive social approval, but still fail to form a strong intention if the behaviour seems difficult or constrained. This logic is highly relevant to workplace AI. Employees may believe that AI tools are useful and may also perceive that colleagues or managers support their use. Nevertheless, they may hesitate if they feel that they lack the necessary technical knowledge, if they are unsure about organisational rules, or if they fear making mistakes. In such cases, low perceived behavioural control can weaken intention even when the other TPB factors are favourable.

Perceived behavioural control is often linked to the concept of self-efficacy. Bandura (1997) defined self-efficacy as people’s beliefs in their capability to organise and execute the actions required to achieve desired outcomes. In technology adoption research, computer self-efficacy has been shown to influence individuals’ willingness to use information systems because users who believe they can handle a technology are more likely to approach it with confidence (Compeau & Higgins, 1995). In the case of AI, this idea can be extended to AI-related self-efficacy. Employees who believe that they can learn AI tools, understand their outputs and manage possible risks are more likely to perceive AI use as controllable.

At the same time, perceived behavioural control is broader than self-efficacy. It includes not only internal capability but also external facilitating conditions. Taylor and Todd (1995), in their decomposed Theory of Planned Behavior, distinguished between self-efficacy, resource facilitating conditions and technology facilitating conditions. This distinction is useful for AI adoption because employees’ perceived control may depend on several external factors. These include whether the organisation provides approved AI tools, whether employees have access to training, whether technical support is available, whether there are clear data protection rules and whether managers allow AI use. An employee may feel personally capable of using AI but still perceive low control if the organisation does not provide access or guidance.

The importance of perceived behavioural control has been confirmed in recent AI adoption research. Srivastava et al. (2024) applied the Theory of Planned Behavior to employees’ AI adoption in the workplace and found that perceived behavioural control, together with attitudes and subjective norms, significantly influenced employees’ intention to use AI at work. This finding is directly relevant to the present dissertation because it shows that employees’ sense of ability and control remains a key predictor of AI adoption intention in an organisational setting.

Perceived behavioural control is also relevant in generative AI adoption. Ivanov et al. (2024) examined generative AI adoption through the lens of the Theory of Planned Behaviour and included perceived behavioural control as one of the core TPB variables associated with intention and actual use. Their study is useful because generative AI tools create both opportunities and risks for users. When users perceive these tools as manageable and feel able to use them appropriately, intention becomes stronger. When the tools are perceived as difficult, risky or insufficiently controllable, intention may weaken.

AI literacy is also closely connected with perceived behavioural control. AI literacy involves the ability to understand, use, evaluate and critically engage with AI systems. It includes knowing what AI can do, recognising its limitations, assessing the quality of AI-generated outputs and understanding ethical issues such as bias, privacy and accountability. Long and Magerko (2020) argue that AI literacy is becoming an important competence as AI systems become more common in everyday life and work. In the workplace, AI literacy can strengthen perceived behavioural control because employees who understand AI tools are more likely to feel capable of using them effectively.

Without such literacy, employees may experience AI as unpredictable or difficult to manage.
Perceived behavioural control may also be influenced by the transparency and explainability of AI systems. When employees understand how a tool works, what data it uses and why it produces certain outputs, they may feel more in control. On the other hand, when AI systems operate as “black boxes”, employees may feel that they cannot evaluate or challenge the outputs. This can reduce perceived control, particularly in professional tasks where accuracy and accountability are important. Glikson and Woolley (2020) show that trust in AI is affected by characteristics such as reliability and transparency. Although trust and perceived control are distinct constructs, they are closely related in practice. Employees are more likely to feel in control when they understand the system and can judge whether its output is dependable.
Organisational policy plays a major role in perceived behavioural control. In many workplaces, employees may be uncertain about whether they are allowed to use public AI tools, what information can be entered into them, and whether AI-generated content must be disclosed or reviewed. This uncertainty can reduce perceived control because employees may fear violating organisational rules. Clear policies can have the opposite effect. When organisations provide explicit guidance on acceptable AI use, data protection, verification requirements and human oversight, employees may feel that AI use is more manageable. The NIST AI Risk Management Framework emphasises the importance of governance, transparency, accountability, privacy and reliability in managing AI risks (NIST, 2023). These principles are relevant because governance structures can increase employees’ confidence that AI use is safe and legitimate.
Training is another critical source of perceived behavioural control. Practical training can help employees move from general awareness of AI to confident and responsible use. Training should not only demonstrate technical functions but also address real work scenarios, limitations, ethical issues and quality control. For example, employees may need to learn how to check AI outputs, avoid sharing sensitive information, identify hallucinations and combine AI-generated material with human judgement. Research on AI in the workplace highlights that skill transformation is a major issue, as employees increasingly need to develop new capabilities to work effectively with AI systems (Babashahi et al., 2024). When training is absent, employees may feel that AI adoption is expected but not adequately supported.
Perceived behavioural control can also be influenced by time and workload. Employees may be willing to learn AI tools but may not feel they have enough time to experiment, practise or integrate them into their workflow. If AI adoption is introduced as an additional demand without reducing other responsibilities, employees may perceive low control. This is relevant to technostress research. Chang et al. (2024) found that AI-driven challenge stressors may promote adoption intention through positive affect, while hindrance stressors may reduce intention by increasing AI anxiety. Their study also showed that technical self-efficacy shapes how employees respond to AI-related demands. In other words, employees are more likely to experience AI as a positive challenge when they feel capable of handling it.
Perceived behavioural control may also affect actual use directly. In the TPB, perceived behavioural control can influence behaviour both through intention and, when it reflects actual control, directly (Ajzen, 1991). This means that employees who feel capable of using AI may not only intend to use it but may also be more likely to act on that

intention. For example, an employee who understands how to use AI safely may quickly incorporate it into routine tasks. By contrast, an employee with low perceived control may continue to avoid AI even when intending to learn it at some point. This highlights why perceived behavioural control is not merely a psychological perception but also a practical condition for implementation.

2.8 Previous Experience with AI Tools

Previous experience with AI tools is an important factor in understanding employees' intention to use artificial intelligence at work, because it reflects the degree to which employees have already interacted with AI-based systems and have formed practical knowledge about their usefulness, limitations and risks. While attitudes, subjective norms and perceived behavioural control explain intention through evaluation, social influence and perceived capability, previous experience adds a more behavioural and experiential dimension. Employees who have already used AI tools are not judging them only through abstract expectations. They have some direct knowledge of what these tools can do, how easy or difficult they are to use, and how relevant they are to their work tasks.

In technology adoption research, prior experience has often been treated as an important determinant of later technology acceptance and continued use. Experience can shape beliefs about usefulness, ease of use, trust, risk and self-efficacy, because users who have interacted with a technology develop more concrete expectations about its performance (Kim & Malhotra, 2005; Venkatesh et al., 2012). This is particularly relevant in the case of AI tools, because many employees may initially have uncertain or mixed perceptions of AI. Some may associate AI with innovation and efficiency, while others may associate it with errors, job insecurity or ethical concerns. Direct experience can either reduce or reinforce these perceptions, depending on whether the interaction with AI is positive, negative or ambiguous.

Previous experience can influence intention in several ways. First, it can increase familiarity. AI tools, especially generative AI systems, may appear complex or unfamiliar to employees who have never used them. Once employees begin to experiment with them, even in simple tasks, the technology may become less intimidating. Familiarity can reduce uncertainty and make AI use feel more manageable. This is consistent with broader technology acceptance literature, which shows that experience can moderate and shape adoption processes over time (Venkatesh et al., 2003; Venkatesh et al., 2012). In practical terms, an employee who has already used AI to summarise a document, draft an email or organise information may be more likely to intend to use it again because the behaviour is no longer abstract.

Second, previous experience can affect perceived usefulness. Employees may hear that AI tools improve productivity, but direct experience allows them to judge whether these benefits apply to their own work. For example, an employee may discover that AI is useful for first drafts, brainstorming, translation or data interpretation, but less useful for tasks requiring highly specific organisational knowledge. This personal evaluation is important because perceived usefulness is one of the most consistent predictors of technology adoption (Davis, 1989; Venkatesh et al., 2003). In the context of workplace AI, experience helps employees move from general beliefs about AI to task-specific judgments about whether AI actually supports their performance.

Third, previous experience can influence perceived ease of use and perceived behavioural control. Employees who have used AI tools before may feel more confident in their ability to use them again. They may have learned how to write better prompts, how to refine outputs, how to check accuracy and how to decide when AI use is appropriate. This confidence is closely related to self-efficacy, which refers to individuals' belief in their ability to perform a behaviour successfully (Bandura, 1997; Compeau & Higgins, 1995). In AI adoption, employees with more experience may feel that they can control the interaction with the tool, while employees with little experience may feel uncertain about how to guide, assess or correct AI-generated responses.

Fourth, previous experience can shape trust. Trust in AI is not created only through organisational communication or technical explanations. It is also built through repeated interaction with AI outputs. When employees repeatedly receive accurate, relevant and useful outputs, they may develop greater trust in the tool. When outputs are inaccurate, irrelevant or difficult to verify, trust may decline. Glikson and Woolley (2020) argue that trust in AI depends on factors such as reliability, transparency, task characteristics and user interaction. This suggests that direct experience is important because it gives employees practical evidence about whether AI can be trusted for particular types of work.

The role of previous experience is also important because AI adoption is often incremental. Employees may first use AI for simple, low-risk tasks before applying it to more complex work. Initial experience may therefore function as a learning stage. If early use is successful, employees may gradually expand their use of AI to additional tasks. This pattern is consistent with innovation diffusion theory, where trialability is one of the characteristics that can support adoption (Rogers, 2003). When employees have opportunities to experiment with AI tools in safe and low-pressure contexts, they can develop familiarity and confidence without feeling that they must immediately transform their entire work routine.

The relationship between previous experience and intention is also connected to habit. In information systems research, repeated use of a technology can create habitual patterns that influence future behaviour beyond conscious intention (Limayem et al., 2007). In the case of AI tools, employees who repeatedly use AI for routine tasks may begin to incorporate it naturally into their workflow. For example, checking an AI tool for a first summary or draft may become part of the employee's normal work process. However, AI use should not become automatic in a way that weakens critical judgement. The professional use of AI requires a balance between familiarity and reflective evaluation. Employees may benefit from routine use, but they also need to remain aware of limitations, bias and possible inaccuracies.

Previous experience may also reduce anxiety. Employees who have never used AI may worry that they will not know how to operate the tool, that they will make mistakes or that AI outputs will be difficult to evaluate. Through experience, these concerns may decrease if employees find that the tool is manageable and that they can maintain control over the final output. Chang et al. (2024) show that AI-related stress can influence adoption intention through affective responses, with technical self-efficacy playing an important role. This suggests that experience can help transform AI from an anxiety-producing technology into a manageable work resource, especially when employees develop confidence through use.

Another important issue is that previous experience may influence how employees respond to social influence. Employees with limited experience may rely more on colleagues, supervisors or organisational expectations when deciding whether to use AI. Because they have not yet developed strong personal beliefs, social cues may be especially important. In contrast, employees with greater AI experience may rely more on their own assessment of the tool. They may be less affected by subjective norms because they already know whether AI is useful for their tasks. This means that previous experience may not only have a direct effect on intention, but may also moderate the relationship between subjective norms and intention. This logic is consistent with technology adoption models in which experience can moderate the effects of social influence and facilitating conditions on behavioural intention and use (Venkatesh et al., 2003; Venkatesh et al., 2012).

Previous experience may also affect attitudes toward AI. Direct use can make attitudes more stable and evidence-based. Employees who have used AI successfully may develop more favourable attitudes because they have observed concrete benefits. Those who have had poor experiences may develop more cautious or negative attitudes. This means that previous experience may operate indirectly through attitudes as well as directly through intention. In other words, experience can influence the beliefs that form attitudes, and these attitudes can then influence intention. This is consistent with Ajzen's (1991) view that behavioural beliefs are shaped by available information and experience.

Previous experience is also linked to the development of AI literacy. Long and Magerko (2020) describe AI literacy as the set of competencies needed to understand and critically interact with AI systems. Experience can support AI literacy by allowing employees to observe how AI behaves in practice. However, experience alone may not be sufficient. Employees may use AI frequently but still misunderstand its limitations. Therefore, experiential learning should be combined with formal guidance on issues such as bias, privacy, explainability and verification. In workplace adoption, the most useful experience is not only frequent use but reflective and informed use.

Recent research on workplace AI adoption also supports the importance of experience-related factors. Nguyen et al. (2026) show that employees' perceptions of AI, including usefulness, ease of use and trust, shape affective attitudes and intentions to use AI at work. Because these perceptions are likely to be influenced by direct interaction with AI tools, previous experience becomes an important background factor in the adoption process. Similarly, studies applying the Theory of Planned Behavior to workplace AI adoption indicate that employees' intention is shaped by personal evaluations, perceived social expectations and perceived control, all of which can be affected by prior exposure to AI (Srivastava et al., 2024).

2.9 Organisational Innovation Support

Organisational innovation support refers to the extent to which employees perceive that their organisation encourages, enables and legitimises the adoption of new ideas, tools and work practices. In the context of AI adoption, this concept is particularly important because employees do not decide whether to use AI tools in a vacuum. Their willingness to experiment with AI, integrate it into work routines and rely on it for specific tasks is shaped by the wider organisational environment. This includes leadership communication, training opportunities, access to approved tools, technical support, psychological safety, innovation climate and clear rules about acceptable AI use. In this sense, organisational innovation support represents the bridge between individual readiness and organisational implementation.

The literature on organisational innovation has long emphasised that employees are more likely to adopt new practices when the workplace provides support for creativity, experimentation and change. Amabile et al. (1996) argued that organisational creativity is influenced by the work environment, including encouragement of creativity, availability of resources and freedom in carrying out tasks. Similarly, Scott and Bruce (1994) showed that innovative behaviour is associated with leadership, work group relations and support for innovation. These findings are relevant to AI adoption because using AI tools often requires employees to test new ways of working, tolerate uncertainty and modify established routines. If the organisation does not support experimentation, employees may avoid AI even when they personally recognise its potential.

Organisational innovation support is also closely related to perceived organisational support. Perceived organisational support refers to employees' general belief that the organisation values their contribution and cares about their well-being (Eisenberger et al., 1986). Although this construct is broader than innovation support, the two are connected. When employees believe that the organisation supports them, provides resources and protects them from unnecessary risk, they may be more willing to engage with new technologies. In AI adoption, this is highly relevant because employees may worry about errors, accountability, data privacy, job security and whether AI use will be judged positively or negatively. Supportive organisations reduce these uncertainties by offering guidance, reassurance and resources.

In the case of artificial intelligence, innovation support is not only a general cultural issue but also a practical implementation condition. AI tools may be technically available, but employees need to know which tools are approved, what tasks are appropriate for AI assistance, how confidential information should be handled and how AI-generated outputs should be reviewed. Without this clarity, employees may experience uncertainty and either avoid AI or use it informally without organisational oversight. Hradecky et al. (2022), in their study of organisational readiness to adopt AI, highlight that AI adoption depends not only on technological readiness but also on organisational capabilities and contextual readiness. This supports the view that organisations need structures, resources and strategic preparation before AI tools can be integrated effectively.

Innovation support is also important because AI adoption often involves changes in work identity and work routines. Employees may need to shift from performing tasks manually to supervising, checking, editing or improving AI-generated outputs. Such changes can create uncertainty, especially when employees are unsure whether AI will enhance or diminish their professional role. Bankins et al. (2024) argue that AI has multilevel implications for organisational behaviour because it affects individuals, teams and organisational systems. From this perspective, organisational innovation support helps employees interpret AI adoption as a collective development process rather than as an isolated technological demand. When AI is introduced through supportive communication and participatory implementation, employees are more likely to perceive it as part of organisational learning.

Leadership plays a central role in organisational innovation support. Managers influence the meaning employees attach to AI by explaining why AI tools are introduced, how they should be used and what benefits or risks should be considered. Supportive leadership does not simply pressure employees to adopt AI. Rather, it creates a safe environment in which employees can ask questions, express concerns and experiment without fear of punishment. Research on implementation climate suggests that employees are more likely to use new practices when they perceive that use is expected, supported and rewarded by the organisation (Klein & Sorra, 1996). In AI adoption, this means that leaders need to make AI use legitimate, but also responsible and bounded by ethical standards.

Training is another key dimension of organisational innovation support. AI tools require more than technical access. Employees need practical and critical understanding of how AI works, what it can do, where it can fail and how its outputs should be evaluated. Babashahi et al. (2024) describe AI in the workplace as part of a broader transformation of skills, where employees increasingly need to combine domain expertise with AI-related competence. Training can therefore increase employees' confidence and reduce uncertainty. It can also prevent misuse by explaining issues such as hallucinations, bias, confidentiality and human oversight. When organisations invest in AI training, employees are more likely to see AI adoption as supported rather than imposed.

Support for innovation also includes the availability of resources. Employees may be willing to use AI tools but unable to do so effectively if they lack access to secure platforms, technical assistance or time to experiment. Resource availability has been identified as an important component of organisational creativity and innovation because employees need both material and psychological conditions to try new methods (Amabile et al., 1996). In AI adoption, resources may include approved AI software, internal guidelines, help desks, peer learning groups, examples of acceptable use and time allocated for training. Without these resources, employees may perceive AI adoption as an additional burden rather than a supportive innovation.

Psychological safety is another important element. AI adoption can involve trial and error, especially when employees are learning how to use new tools. If employees fear that mistakes will be punished or that asking for help will reveal incompetence, they may be reluctant to experiment. Edmondson (1999) conceptualised psychological safety as a shared belief that the team is safe for interpersonal risk-taking. In AI adoption, this means that employees should feel able to discuss uncertainties, report problems and challenge AI outputs without embarrassment or fear. A psychologically safe environment can make AI experimentation more constructive and reduce resistance based on fear or uncertainty.

Organisational innovation support is also linked to trust. Employees may be more willing to use AI when they trust not only the tool but also the organisation's intentions in introducing it. If AI is presented mainly as a way to monitor employees, reduce staff or intensify workload, innovation support is likely to be perceived as weak. If AI is presented as a tool for improving work quality, reducing repetitive tasks and supporting employee capability, employees may respond more positively. Glikson and Woolley (2020) note that trust in AI depends partly on the context in which AI is used. In organisational settings, that context includes leadership, communication, policies and the perceived fairness of implementation.

Clear governance is especially important for AI-related innovation support. AI tools can create risks related to privacy, bias, explainability, accuracy and accountability. Employees may hesitate to use AI if they are uncertain about who is responsible for the final output or whether the use of AI is allowed in sensitive tasks. The NIST AI Risk

Management Framework stresses the importance of governance, transparency, accountability, privacy and fairness in AI systems (NIST, 2023). Although this is a risk-management framework rather than an employee adoption model, it is relevant because organisational governance can strengthen employees' sense that AI use is safe, legitimate and professionally appropriate.

Recent research also connects organisational support with employees' AI acceptance. Feng et al. (2025) examined how multidimensional organisational support influences employees' acceptance of AI technologies, focusing on technostress and innovation resistance as mediating mechanisms. Their work highlights that organisational support can reduce negative reactions to AI and improve acceptance by addressing the psychological and practical barriers employees face. This is directly relevant to the present study because innovation support may shape whether employees experience AI as a useful organisational resource or as a disruptive demand.

Organisational support may also influence AI adoption through digital culture. A digital culture is characterised by openness to technological change, learning orientation, data-informed decision-making and willingness to experiment with digital tools. When such a culture exists, AI adoption is more likely to be viewed as a natural extension of existing work practices. Conversely, when the organisational culture is risk-averse or resistant to change, employees may perceive AI as incompatible with established norms. Studies of organisational AI readiness emphasise that readiness includes not only technical infrastructure but also strategy, skills, leadership and culture (Hradecky et al., 2022). This suggests that organisational innovation support should be understood as a multidimensional condition, not simply as managerial encouragement.

In the present study, organisational innovation support is treated as a contextual control variable rather than as a core component of the TPB model. This approach allows the study to acknowledge the organisational environment in which AI adoption takes place, without shifting the main focus away from the behavioural predictors of intention, namely attitudes, subjective norms, perceived behavioural control and previous AI experience.

2.10 Review of Previous Empirical Studies

Previous empirical research on AI adoption shows that employees' intention to use AI tools is shaped by a combination of individual, social and organisational factors. Although early technology adoption studies focused mainly on traditional information systems, recent studies examine AI as a more complex workplace technology because it involves usefulness, trust, uncertainty, skill requirements, ethical concerns and possible changes in professional roles.

A central empirical foundation comes from technology acceptance research. Davis (1989) showed that perceived usefulness and perceived ease of use influence users' acceptance of information systems, while Venkatesh et al. (2003) later proposed that performance expectancy, effort expectancy, social influence and facilitating conditions predict behavioural intention and use. These models are not AI-specific, but they remain relevant because employees usually evaluate AI tools according to whether they improve performance, are easy to use, are socially supported and can be used under appropriate workplace conditions.

More recent studies have applied these ideas directly to AI. Srivastava et al. (2024) examined AI adoption in the workplace using the Theory of Planned Behavior and found that attitudes, subjective norms and perceived behavioural control significantly influenced employees' intention to use AI at work. This finding is particularly important for the present dissertation because it confirms that the TPB is suitable for studying workplace AI adoption and that intention is shaped by personal evaluation, social expectations and perceived capability.

Nguyen et al. (2026) examined employees' perceptions of AI in the workplace using data from 1,224 working adults. Their study showed that trust in AI, perceived usefulness and perceived ease of use influence affective attitudes toward AI, which then shape employees' intention to adopt AI in their job. This is relevant because it suggests that employees' intention is not only the result of rational evaluation, but also of affective reactions toward AI use.

Generative AI adoption has also been examined through behavioural models. Ivanov et al. (2024) studied generative AI adoption in higher education through the lens of the TPB. They found that perceived benefits, strengths, weaknesses and risks of generative AI are associated with the TPB constructs, namely attitude, subjective norms and perceived behavioural control, which then relate to intention and actual use. Although their study is not focused on employees, it is useful for the present research because generative AI tools are now widely used for work-related tasks such as writing, summarising, translating and decision support.

Another relevant empirical direction concerns AI-related stress and confidence. Chang et al. (2024) found that AI-driven challenge stressors can increase adoption intention through positive affect, while hindrance stressors can reduce intention through AI anxiety. Their findings also showed the importance of technical self-efficacy. This indicates that employees may respond positively to AI when they perceive it as a manageable learning opportunity, but negatively when they experience it as threatening or overwhelming.

The role of trust has also been highlighted in empirical and review-based studies. Glikson and Woolley (2020) showed that trust in AI depends on factors such as reliability, transparency, task type and user expectations. In workplace settings, this is important because employees remain responsible for the quality of their work even when AI tools support their decisions. Therefore, lack of trust may reduce positive attitudes and weaken intention to use AI tools.

Other studies have focused on the organisational side of AI adoption. Hradecky et al. (2022) argued that organisational readiness for AI adoption depends not only on technology, but also on strategy, resources, capabilities and organisational context. This supports the view that employees' intention to use AI may be stronger when the organisation provides training, approved tools, clear guidelines and a supportive innovation climate.

Overall, the empirical literature suggests that AI adoption at work cannot be explained by one factor alone. Attitudes are important because employees need to evaluate AI as useful and beneficial. Subjective norms matter because workplace AI use is socially shaped by colleagues, supervisors and organisational expectations. Perceived behavioural control is important because employees must feel capable of using AI tools effectively and responsibly. Previous experience with AI can reduce uncertainty and strengthen confidence, while organisational innovation support can make AI use more legitimate and feasible.

2.11 Research Model and Hypotheses Development

The research model of the present dissertation is based on the Theory of Planned Behavior and is adapted to the context of AI tool use in the workplace. The dependent variable is employees' intention to use AI tools at work. The main predictors are attitudes toward AI tools, subjective norms, perceived behavioural control and previous experience with AI tools. In addition, the model examines whether previous AI experience moderates the relationship between subjective norms and intention.

The first hypothesis concerns attitudes toward AI tools. According to the TPB, individuals are more likely to intend to perform a behaviour when they evaluate it positively (Ajzen, 1991). In the context of this study, employees who believe that AI tools are useful, efficient and beneficial for their work are expected to report stronger intention to use them. This is also consistent with recent empirical research showing that positive attitudes and perceived usefulness are important predictors of AI adoption intention.

H1: Attitudes toward AI tools have a positive effect on employees' intention to use AI tools at work.

The second hypothesis concerns subjective norms. In the workplace, employees may be influenced by the expectations of colleagues, supervisors, managers and the broader organisational environment. When AI use is perceived as socially accepted or encouraged, employees may be more willing to adopt it. Previous AI adoption research based on the TPB has confirmed the positive role of subjective norms in intention to use AI at work.

H2: Subjective norms have a positive effect on employees' intention to use AI tools at work.

The third hypothesis concerns perceived behavioural control. Employees are more likely to intend to use AI tools when they feel that they have the knowledge, skills, access, time and support needed to use them properly. This is particularly important in AI adoption because effective use requires not only technical access but also confidence in evaluating AI-generated outputs and using them responsibly. Empirical studies on AI and generative AI adoption support the relevance of perceived behavioural control in explaining intention.

H3: Perceived behavioural control is positively associated with employees' intention to use AI tools at work.

The fourth hypothesis concerns previous experience with AI tools. Employees who have already used AI tools may have clearer perceptions of their usefulness, limitations and risks. Previous experience can reduce uncertainty, increase familiarity and strengthen confidence. Therefore, employees with greater AI experience are expected to show stronger intention to use AI tools at work.

H4: Previous experience with AI tools is positively associated with employees' intention to use AI tools at work.

The final hypothesis concerns the moderating role of previous AI experience. Employees with limited AI experience may rely more strongly on social cues, such as whether colleagues or supervisors approve of AI use. By contrast, employees with more experience may base their intention more on their own practical evaluation of AI tools.

Therefore, previous AI experience is expected to influence the strength of the relationship between subjective norms and intention.
Previous AI experience is also expected to influence the strength of the relationship between subjective norms and intention. Employees with limited experience with AI tools may rely more heavily on social cues from colleagues, supervisors and managers, because they have not yet formed a stable personal evaluation of AI use. In this case, subjective norms can provide guidance about whether AI use is appropriate, useful or professionally accepted. By contrast, employees with higher AI experience are more likely to have developed their own judgement about the usefulness, limitations and risks of AI tools. As a result, their intention to use AI may depend less on social expectations and more on their direct experience with the technology.

H5: Previous AI experience moderates the relationship between subjective norms and employees' intention to use AI tools at work, such that the positive association between subjective norms and intention is expected to be stronger among employees with lower AI experience and weaker among employees with higher AI experience.

The proposed model therefore combines personal, social and experiential factors. Attitudes capture employees' evaluation of AI tools, subjective norms capture perceived social influence, perceived behavioural control captures perceived capability and resources, and previous AI experience captures direct familiarity with AI tools. Organisational innovation support remains relevant as part of the wider organisational context, but the core predictive model focuses on the variables tested in the regression and moderation analysis of the present study .

3 Chapter 3: Methodology

3.1 Research Design

The present study adopted a quantitative, cross-sectional research design in order to investigate the factors that influence employees' intention to use artificial intelligence tools in the workplace. A quantitative design was considered appropriate because the study aimed to examine measurable relationships between predefined variables, namely attitudes toward AI tools, subjective norms, perceived behavioural control, previous experience with AI tools, organisational innovation support and intention to use AI tools at work.

The study was cross-sectional, as data were collected at one specific point in time from a sample of participants. This design allowed the researcher to capture employees' perceptions, beliefs and intentions regarding the use of AI tools in their current work context. Although a cross-sectional design does not allow causal conclusions in the strict sense, it is suitable for examining associations between variables and testing theoretically grounded hypotheses based on the Theory of Planned Behavior.

The research design was explanatory in nature. More specifically, the study did not aim only to describe employees' views about AI, but also to examine which factors predict their intention to use AI tools at work. For this reason, statistical analyses such as correlation analysis, multiple linear regression and moderation analysis were used. In addition, confirmatory factor analysis was conducted in order to examine the measurement structure of the main constructs included in the study.

Because the study followed a cross-sectional design, all variables were measured at the same point in time. Therefore, the findings should be interpreted as statistical associations rather than causal relationships. The regression results indicate which variables statistically predict intention within the sample, but they do not establish causal effects.

3.2 Research Approach

The study followed a deductive research approach. The deductive approach begins with an existing theoretical framework and uses empirical data to test relationships derived from that framework. In the present dissertation, the main theoretical foundation was the Theory of Planned Behavior, according to which behavioural intention is influenced by attitudes, subjective norms and perceived behavioural control (Ajzen, 1991). This theoretical model was adapted to the context of AI tool use in the workplace.

The deductive approach was appropriate because the study was based on specific hypotheses developed from the literature review. These hypotheses concerned the expected positive effects of attitudes, subjective norms, perceived behavioural control and previous AI experience on employees' intention to use AI tools. The study also examined the moderating role of previous AI experience in the relationship between subjective norms and intention.

The research approach was also positivist in orientation, as it relied on numerical data, standardised measurement, statistical analysis and hypothesis testing. Participants' responses were converted into numerical values and analysed using statistical software. This approach allowed the researcher to identify patterns in the data and assess the strength and significance of the relationships between the variables.

3.3 Population and Sample

The target population of the study consisted of employees who could potentially use AI tools in their professional activities. The study focused on employees because the research objective was to examine AI adoption in work-related contexts rather than general or recreational AI use. Participants were therefore individuals with work experience or current professional involvement, who were able to express views about the possible use of AI tools in their job.

The final sample consisted of 104 participants, as indicated in the statistical analysis output . The sample included both men and women, with a very balanced gender distribution. Based on the raw questionnaire responses, women represented 50.0% of the sample, men represented 49.0%, while 1.0% of participants preferred not to answer. Participants' age ranged from 21 to 78 years, with a mean age of 38.02 years and a standard deviation of 9.26.

Regarding educational level, most participants had a high level of education. The largest group held a postgraduate degree, followed by participants with a university or technological education degree. A smaller proportion of the sample had completed secondary education, while very few participants selected "other" or doctoral-level education. In relation to previous experience with AI tools, the sample included participants with different levels of familiarity, ranging from no experience to high

experience. This variation was useful for the purposes of the study, as previous AI experience was one of the key variables examined.
The sampling method was non-probability convenience sampling. This method was selected because it enabled the researcher to collect data from available participants who met the basic inclusion criterion, namely the ability to respond to questions about AI tools and their possible use in work. Although convenience sampling limits the generalisability of the findings, it is commonly used in survey-based studies where the aim is to explore relationships between psychological and organisational variables.

3.4 Data Collection Procedure

Data were collected through a structured self-completion questionnaire. The questionnaire was designed to measure participants' demographic characteristics, previous experience with AI tools and their perceptions regarding the use of AI in the workplace. Participation was voluntary, and respondents were asked to answer all questions based on their own views and experiences.
Before completing the questionnaire, participants were informed about the purpose of the study and the general topic of the research. They were also informed that their responses would be used only for academic purposes and would be analysed anonymously. No identifying personal information was required, which helped protect participants' privacy and confidentiality.
The questionnaire was distributed electronically, allowing participants to complete it at a time and place convenient for them. This method was suitable because the topic of the study concerned digital technologies and AI tools, and the online format made it easier to reach participants from different professional backgrounds. The use of a standardised questionnaire also ensured that all participants received the same questions in the same order, which strengthened the consistency of the data collection process.
After data collection was completed, the responses were exported and prepared for statistical analysis. The variables were coded numerically, and scale scores were computed for the main constructs. The final dataset included the demographic variables, previous AI experience and the questionnaire items measuring attitudes, subjective norms, perceived behavioural control, intention to use AI tools and organisational innovation support.

3.5 Research Instrument

The research instrument was a structured questionnaire developed for the purposes of the present study. The questionnaire was based on the theoretical framework of the Theory of Planned Behavior and on the wider literature on technology and AI adoption. It included items measuring attitudes toward AI tools, subjective norms, perceived behavioural control, intention to use AI tools, organisational innovation support and previous experience with AI.
The questionnaire consisted of closed-ended questions. The first part included demographic questions, such as gender, age and educational level. It also included a question measuring participants' previous experience with AI tools. The second part included statements related to the main constructs of the study. Participants were asked

to indicate their level of agreement with each statement using a Likert-type response scale.
The Likert-type scale allowed participants to express the degree to which they agreed or disagreed with each statement. This type of scale was appropriate because the study aimed to measure perceptions, evaluations and intentions, which are commonly assessed through agreement-based items in behavioural and organisational research. Higher scores indicated more positive attitudes, stronger subjective norms, higher perceived behavioural control, stronger intention to use AI tools or stronger perceived organisational innovation support.
The questionnaire included the following main groups of items:

- Attitudes toward AI tools were measured with four items.
- Subjective norms were measured with two items.
- Perceived behavioural control was measured with three items.
- Intention to use AI tools was measured with three items.
- Organisational innovation support was measured with four items.
- Previous AI experience was measured with one item.

The structure of the measurement model was later examined through confirmatory factor analysis, and the internal consistency of the scales was assessed through Cronbach's alpha and McDonald's omega.

3.6 Data Analysis Strategy

The data were analysed using statistical procedures appropriate for the research questions and hypotheses of the study. The analysis was conducted using jamovi and relevant statistical modules. The statistical output shows that the analysis included descriptive statistics, reliability analysis, confirmatory factor analysis, correlation analysis, multiple linear regression and moderation analysis .
First, descriptive statistics were calculated for the demographic variables and the main study variables. Means, standard deviations, minimum and maximum values were used to describe the central tendency and variability of the variables. The descriptive analysis provided an overview of participants' age, previous AI experience and mean scores on attitudes, subjective norms, perceived behavioural control, intention and innovation support.
Second, reliability analysis was conducted in order to examine the internal consistency of the scales. Cronbach's alpha and McDonald's omega were used as reliability indicators. These indices were selected because they provide information about the extent to which the items of each scale measure the same underlying construct.
Third, confirmatory factor analysis was conducted to examine the measurement structure of the questionnaire. The five-factor model included attitudes, subjective norms, perceived behavioural control, intention and organisational innovation support. Model fit was assessed using common fit indices, including CFI, TLI, SRMR and RMSEA. In addition, Harman's one-factor test was conducted to assess whether common method bias was likely to be a serious problem.

Fourth, correlation analysis was used to examine bivariate relationships between the main variables. This analysis helped identify the direction and strength of associations among previous AI experience, attitudes, subjective norms, perceived behavioural control and intention to use AI tools.

Fifth, multiple linear regression analysis was conducted to test the predictive role of the TPB variables. In the basic model, intention to use AI tools was regressed on attitudes, subjective norms and perceived behavioural control. In the extended model, previous AI experience was added as an additional predictor. In addition to the main TPB predictors and previous AI experience, organisational innovation support was included as a control variable in an additional regression model. This was done because innovation support reflects the organisational context within which employees form their intention to use AI tools. The purpose of including this variable was not to treat it as a central TPB predictor or as a moderator, but to examine whether the effects of attitudes, subjective norms, perceived behavioural control and previous AI experience remained stable after accounting for the perceived innovation climate of the organisation. Finally, a moderation model was tested by adding the interaction term between subjective norms and previous AI experience.

The moderation analysis examined whether the relationship between subjective norms and intention differed depending on participants' level of previous AI experience. Simple effects were then used to interpret the interaction at low, average and high levels of previous AI experience.

3.7 Reliability and Validity Testing

Reliability and validity testing were conducted to assess the quality of the measurement instrument. Reliability was examined using Cronbach's alpha and McDonald's omega. These indicators were used to determine whether the items within each scale showed acceptable internal consistency.

The statistical output showed that several scales demonstrated good reliability. For example, the attitude scale had high reliability, while the intention and innovation support scales also showed strong internal consistency. The subjective norms and perceived behavioural control scales showed lower but still usable levels of reliability, which may be partly related to the small number of items included in these scales. This is particularly relevant for subjective norms, which was measured with only two items.

Construct validity was examined through confirmatory factor analysis. The CFA tested whether the observed questionnaire items loaded on their expected latent constructs. The results showed that most standardised factor loadings were acceptable to strong, particularly for attitudes, intention and innovation support. The model fit indices indicated an acceptable, although not perfect, fit of the five-factor measurement model. The CFI value was above .90, while the SRMR value was below .08. The RMSEA value was somewhat higher than ideal, which suggests that the measurement model should be interpreted with some caution. Nevertheless, the overall CFA results supported the distinction between the main constructs.

Common method bias was assessed through Harman's one-factor test. The one-factor model showed clearly poorer fit compared with the multi-factor model. This suggests that a single general factor did not adequately explain the covariance among the items and that common method bias was unlikely to fully account for the observed relationships

Overall, the reliability and validity testing supported the use of the questionnaire for the purposes of the study, while also indicating some limitations in specific scales that should be acknowledged in the interpretation of the results.

3.8 Ethical Considerations

The study followed basic ethical principles for research with human participants. Participation was voluntary, and respondents were informed about the academic purpose of the study before completing the questionnaire. Participants were not required to provide identifying personal information, and their responses were analysed anonymously.

Confidentiality was maintained throughout the research process. The data were used only for the purposes of the present dissertation and were not shared with third parties. The results were reported in aggregate form, meaning that no individual participant could be identified from the analysis or discussion of findings.

Participants had the right to choose whether to participate in the study and could stop completing the questionnaire if they did not wish to continue. The questionnaire did not include questions of a highly sensitive personal nature. Nevertheless, care was taken to ensure that the data were handled responsibly and that participants' privacy was respected.

The study also considered the ethical use of data in relation to AI-related research. Since the topic concerns employees' perceptions of AI tools, it was important to avoid collecting unnecessary personal information. The research focused on attitudes, perceptions, experience and intention rather than on evaluating individual performance or workplace behaviour. This helped minimise potential risks to participants.

4 Chapter 4: Results

This chapter presents the empirical results of the study on the factors that influence employees' intention to use AI tools at work. The analysis was conducted on a sample of 104 participants. The results are presented in a sequence that follows the logic of the research model. First, the measurement model is examined through confirmatory factor analysis and reliability testing. Then, descriptive statistics and correlations are reported. Finally, the regression models are presented, including the basic Theory of Planned Behavior model, the extended model with previous AI experience, and the moderation model testing the interaction between subjective norms and previous AI experience.

Abbreviations used in this chapter: ATT = Attitudes toward AI tools; SN = Subjective Norms; PCB = Perceived Behavioural Control; INT = Intention to use AI tools; INSUPP/InovSupp = Organisational Innovation Support; expAI = Previous AI Experience.

4.1 Confirmatory Factor Analysis of the Measurement Model

A confirmatory factor analysis (CFA) was conducted in order to examine whether the observed questionnaire items loaded on the expected latent constructs. The tested measurement model included five latent variables: attitudes toward AI tools, subjective norms, perceived behavioural control, intention to use AI tools, and organisational innovation support. The CFA results showed that most standardised factor loadings were acceptable to strong, indicating that the items generally represented their intended constructs. For attitudes, the standardised loadings ranged from .762 to .919, suggesting a strong measurement structure. Intention also presented strong loadings, ranging from .769 to .880. The organisational innovation support items loaded between .669 and .834, which also indicates adequate convergence. Subjective norms presented acceptable loadings (.641 and .788), while perceived behavioural control had weaker but still interpretable loadings, ranging from .495 to .722.

Table 4.1. Standardised factor loadings from the confirmatory factor analysis

Latent factor	Item	Standardised loading
Attitudes	ATT1	.817
Attitudes	ATT2	.816
Attitudes	ATT3	.762
Attitudes	ATT4	.919
Subjective Norms	SN1	.641
Subjective Norms	SN2	.788
Perceived Behavioural Control	PCB1	.507
Perceived Behavioural Control	PCB2	.495
Perceived Behavioural Control	PCB3	.722
Intention	INT1	.769
Intention	INT2	.829
Intention	INT3	.880
Innovation Support	INSUP1	.806
Innovation Support	INSUP2	.834
Innovation Support	INSUP3	.669
Innovation Support	INSUP4	.749

Note. All loadings were statistically significant at $p < .001$.

Regarding model fit, the five-factor CFA model produced CFI = .907, TLI = .882, SRMR = .069 and RMSEA = .093, with a 90% confidence interval for RMSEA from .072 to .114. The CFI value was above .90 and the SRMR value was below .08, while the TLI was slightly below the conventional .90 threshold and the RMSEA value was somewhat elevated. Therefore, the fit of the measurement model should be interpreted as mixed but sufficiently usable for the purposes of the present analysis, rather than as excellent. This is not unexpected in applied survey research, especially with a moderate sample size and constructs measured with a small number of items. The CFA path diagram is presented in Figure 4.1. The diagram visually confirms that each group of items was linked to its respective latent construct.

Fit Measures

				RMSEA 90% CI	
CFI	TLI	SRMR	RMSEA	Lower	Upper
0.907	0.882	0.0690	0.0930	0.0720	0.114

Path Diagram

[4]

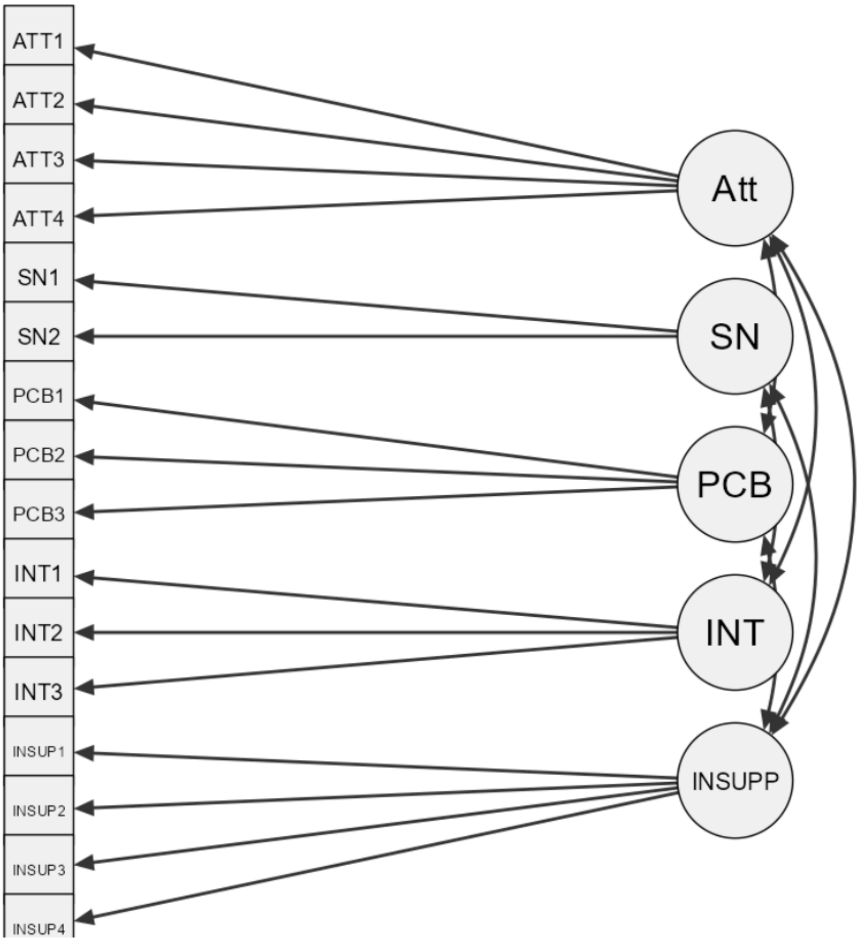

Figure 4.1. Confirmatory factor analysis path diagram for the five-factor measurement model

4.2 Assessment of Common Method Bias: Harman's One-Factor Test

Because the data were collected through a self-report questionnaire, common method bias was examined using Harman's one-factor test. A one-factor CFA model was estimated in which all measurement items were forced to load on a single latent factor. If a single-factor model had fitted the data well, this would have suggested that common method variance might be a serious concern. However, the results of the one-factor model were clearly weaker than those of the five-factor measurement model. The one-factor model produced $\chi^2(104) = 434$, $p < .001$, CFI = .638, TLI = .583, SRMR = .140 and RMSEA = .175, with a 90% confidence interval from .158 to .192. These fit indices indicate poor model fit and show that the data are not adequately represented by one general factor.

[4]

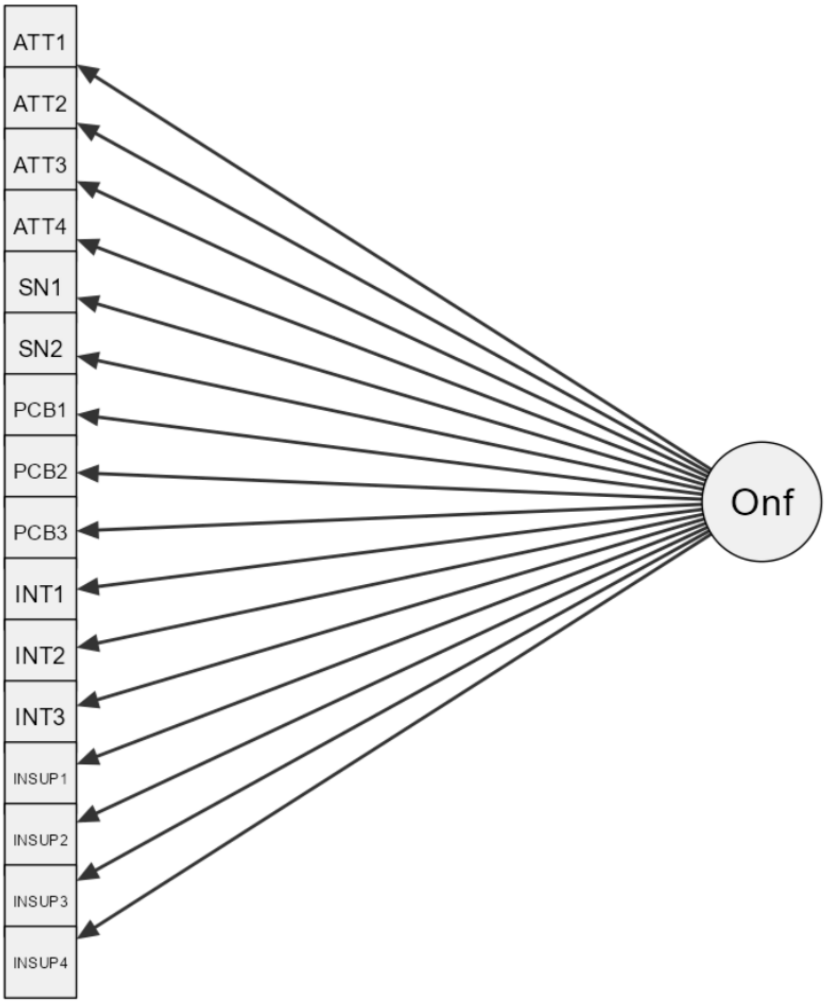

Figure 4.2. One-factor model used for Harman's test

The comparison between the five-factor model and the one-factor model supports the discriminant structure of the questionnaire. Although common method bias cannot be ruled out completely through this test alone, the poor fit of the one-factor model suggests that the observed items are not adequately represented by a single general factor. Therefore, the subsequent analyses can proceed with greater confidence that the measured constructs are empirically distinguishable.

4.3 Reliability Analysis

Internal consistency was examined using Cronbach's alpha and McDonald's omega. The reliability results indicated good internal consistency for attitudes, intention and organisational innovation support. The attitudes scale showed the highest reliability, with Cronbach's alpha = .897 and omega = .898. Intention also demonstrated strong reliability, with alpha = .856 and omega = .865. Organisational innovation support presented similarly strong reliability, with alpha = .851 and omega = .853. The subjective norms scale showed acceptable but lower reliability, with alpha = .671 and omega = .672. The perceived behavioural control scale presented the weakest reliability, with alpha = .606 and omega = .615. This suggests that the interpretation of perceived behavioural control should be made with some caution, as the items may not have captured the construct as consistently as the other scales.

Table 4.2. Reliability coefficients for the main scales

Scale	Cronbach's alpha	McDonald's omega
Attitudes	.897	.898
Subjective Norms	.671	.672
Perceived Behavioural Control	.606	.615
Intention	.856	.865
Organisational Innovation Support	.851	.853

4.4 Descriptive Statistics

Descriptive statistics were calculated for the demographic variables and the main study variables. The mean age of the participants was 38.02 years (SD = 9.26), with ages ranging from 21 to 78 years. Previous experience with AI had a mean of 3.37 (SD = 1.09) on a scale from 1 to 5, suggesting a moderate level of prior exposure to AI tools. Among the main psychological constructs, attitudes toward AI tools had the highest mean value (M = 3.96, SD = .69), indicating that participants generally evaluated AI tools positively. Intention to use AI tools was also relatively high (M = 3.80, SD = .83). Perceived behavioural control had a mean of 3.65 (SD = .78), while subjective norms had a lower mean of 3.41 (SD = .76). Organisational innovation support had the lowest mean among the main scales (M = 3.23, SD = .91), suggesting that participants perceived their organisational environment as only moderately supportive of innovation and AI-related change.

Table 4.3. Descriptive statistics and Shapiro-Wilk tests

Variable	Mean	SD	Minimum	Maximum	W	p
sex	.500	.502	0	1	.636	< .001
age	38.019	9.260	21	78	.954	.001
edu	1.577	.602	0	2	.672	< .001
expAI	3.365	1.089	1	5	.909	< .001
ATT	3.962	.692	1.75	5.00	.920	< .001
SN	3.409	.759	1.50	5.00	.943	< .001
PCB	3.651	.783	1.67	5.00	.945	< .001
INT	3.795	.829	1.33	5.00	.942	< .001
InovSupp	3.228	.911	1.00	5.00	.970	.019

Note. The Shapiro-Wilk tests indicated deviations from normality for several raw variables; therefore, the interpretation of the inferential results also considers the regression assumption checks reported below.

4.5 Correlation Analysis

The correlation matrix showed several statistically significant relationships among the main variables. The strongest association was observed between attitudes and intention to use AI tools ($r = .744$, $p < .001$). This indicates that participants who evaluated AI tools more positively also reported stronger intention to use them at work. Previous AI experience was also positively correlated with intention ($r = .550$, $p < .001$), suggesting that employees with greater previous exposure to AI tools tended to report higher intention to use them. Subjective norms were positively related to intention ($r = .567$, $p < .001$), while perceived behavioural control was also positively related to intention ($r = .513$, $p < .001$). These results provide initial support for the proposed relationships before the regression models are examined.

Table 4.4. Statistically significant correlations among the study variables

Variables	Correlation coefficient	Significance
edu with age	.198	*
ATT with edu	.234	*
ATT with expAI	.463	***
SN with expAI	.352	***
SN with ATT	.494	***
PCB with expAI	.546	***
PCB with ATT	.432	***
PCB with SN	.436	***
INT with edu	.239	*
INT with expAI	.550	***
INT with ATT	.744	***
INT with SN	.567	***
INT with PCB	.513	***

*Note. Only statistically significant correlations from the output are displayed. * p < .05, *** p < .001.*

4.6 4.6 Regression Analysis: Basic Theory of Planned Behavior Model

The first regression model examined the basic Theory of Planned Behavior predictors of intention to use AI tools. Attitudes, subjective norms and perceived behavioural control were entered as predictors of intention. The overall model was statistically significant, $R = .793$, $R^2 = .629$, adjusted $R^2 = .618$, $F(3, 100) = 56.6$, $p < .001$. This means that the three TPB predictors explained 62.9% of the variance in employees' intention to use AI tools. All three predictors were statistically significant in the basic model. Attitudes were the strongest predictor ($B = .673$, $\beta = .562$, $t = 7.71$, $p < .001$), followed by subjective norms ($B = .230$, $\beta = .211$, $t = 2.88$, $p = .005$) and perceived behavioural control ($B = .189$, $\beta = .179$, $t = 2.54$, $p = .013$). The results therefore show that, before including additional predictors, employees' intention to use AI tools was higher when they had more favourable attitudes, perceived stronger social encouragement and felt greater control over using AI tools.

Table 4.5. Regression coefficients for the basic TPB model predicting intention

Predictor	B	SE	t	p	Standardised beta
ATT	.673	.0873	7.71	< .001	.562
SN	.230	.0797	2.88	.005	.211
PCB	.189	.0745	2.54	.013	.179

Note. Model fit: R = .793, R^2 = .629, adjusted R^2 = .618, F(3, 100) = 56.6, p < .001.

The assumption checks supported the adequacy of the basic regression model. The residuals did not significantly deviate from normality, as indicated by Shapiro-Wilk p = .864, Kolmogorov-Smirnov p = .892 and Anderson-Darling p = .604. The heteroskedasticity tests were also non-significant, including Breusch-Pagan p = .559, Goldfeld-Quandt p = .515 and Harrison-McCabe p = .506. In addition, the VIF values ranged from 1.34 to 1.44, indicating no problematic multicollinearity among the three predictors in the basic model.

4.7 Extended Regression Model with Previous AI Experience

The second model added previous AI experience to the basic TPB predictors. The inclusion of previous AI experience improved the explanatory power of the model. The model fit increased from R^2 = .629 to R^2 = .651, and this change was statistically significant, ΔR^2 = .0218, F(1, 99) = 6.18, p = .015. Thus, previous AI experience explained additional variance in intention beyond attitudes, subjective norms and perceived behavioural control.

In the extended model, attitudes remained the strongest predictor of intention (B = .614, β = .513, t = 6.960, p < .001). Subjective norms also remained statistically significant (B = .222, β = .203, t = 2.849, p = .005). Previous AI experience was a significant positive predictor (B = .141, β = .185, t = 2.487, p = .015), indicating that employees with greater previous exposure to AI reported higher intention to use AI tools at work. However, perceived behavioural control was no longer statistically significant once previous AI experience was included (B = .108, β = .102, t = 1.362, p = .176). This suggests that part of the initial effect of perceived behavioural control may overlap with previous AI experience, as employees with more experience may also feel more capable of using AI tools.

Table 4.6. Regression coefficients for the extended model including previous AI experience

Predictor	B	SE	t	p	Standardised beta
ATT	.614	.0883	6.960	< .001	.513
SN	.222	.0778	2.849	.005	.203
PCB	.108	.0796	1.362	.176	.102
expAI	.141	.0566	2.487	.015	.185

Note. Model fit: R = .807, R^2 = .651, adjusted R^2 = .637, F(4, 99) = 46.2, p < .001. Change from Model 1: ΔR^2 = .0218, p = .015.

The assumption checks for the extended model were also satisfactory. The residual normality tests were non-significant, including Shapiro-Wilk p = .376, Kolmogorov-Smirnov p = .845 and Anderson-Darling p = .227. The heteroskedasticity tests were also non-significant, including Breusch-Pagan p = .864, Goldfeld-Quandt p = .730 and

Harrison-McCabe p = .735. The VIF values ranged from 1.44 to 1.60, showing that multicollinearity was not a concern in the extended model without the interaction term.

4.8 Moderation Analysis: Subjective Norms and Previous AI Experience

The final moderation model included attitudes, subjective norms, perceived behavioural control, previous AI experience, organisational innovation support as a control variable, and the interaction term between subjective norms and previous AI experience. Organisational innovation support was included in order to examine whether the main findings remained stable after accounting for the perceived innovation climate of the organisation. The overall model was statistically significant. Because the study is cross-sectional, the regression coefficients are interpreted as statistical associations within the present sample rather than as causal effects.

Attitudes remained the strongest positive predictor of intention (B = .649, beta = .542, $p < .001$). Previous AI experience was also positively associated with intention (B = .126, beta = .165, p = .023). Organisational innovation support was statistically significant (B = .152, beta = .167, p = .019), indicating that employees who perceived stronger organisational support for innovation also reported stronger intention to use AI tools. Perceived behavioural control was not statistically significant (B = .081, beta = .076, p = .307). The main effect of subjective norms was marginally non-significant in this final model (B = .150, beta = .138, p = .074). Importantly, the interaction between subjective norms and previous AI experience was negative and statistically significant (B = -.157, beta = -.157, p = .013), indicating that the association between subjective norms and intention was weaker at higher levels of previous AI experience.

Table 4.7. Final moderated regression model predicting intention, controlling for organisational innovation support

Predictor	B	SE	95% CI Lower	95% CI Upper	beta	t	p
ATT	.649	.087	.476	.821	.542	7.468	< .001
SN	.150	.083	-.015	.316	.138	1.806	.074
PCB	.081	.078	-.075	.236	.076	1.026	.307
expAI	.126	.055	.017	.234	.165	2.304	.023
InovSupp	.152	.064	.026	.278	.167	2.386	.019
SN x expAI	-.157	.062	-.281	-.034	-.157	-2.537	.013

Note. Organisational innovation support was entered as a contextual control variable. All continuous covariates were mean-centred in the moderation analysis. B = unstandardised coefficient; beta = standardised coefficient.

The final moderation results should be interpreted with appropriate caution. Product terms in moderation models can be correlated with their component variables, even after mean-centering. The statistical significance and direction of the interaction are therefore reported together with the confidence interval, rather than being interpreted as evidence of a causal mechanism.

4.9 Summary of Hypothesis Testing

The results provide strong support for the central role of attitudes in statistically predicting employees' intention to use AI tools at work. Across the regression models, attitudes were the strongest and most stable predictor of intention. Subjective norms were statistically significant in the basic and extended models, but their direct effect became marginally non-significant in the final moderated model controlling for organisational innovation support. Previous AI experience was positively associated with intention and moderated the relationship between subjective norms and intention in the expected negative direction. Perceived behavioural control was statistically significant in the basic TPB model but became non-significant after previous AI experience was added. Organisational innovation support was included as a contextual control variable in the final model and was positively associated with intention.

Table 4.8. Summary of hypothesis testing

Hypothesis	Statement	Result
H1	Attitudes are positively associated with intention to use AI tools.	Supported
H2	Subjective norms are positively associated with intention to use AI tools.	Supported in basic and extended models; marginally non-significant in final model
H3	Perceived behavioural control is positively associated with intention to use AI tools.	Partially supported
H4	Previous AI experience is positively associated with intention to use AI tools.	Supported
H5	Previous AI experience moderates the relationship between subjective norms and intention, such that the positive association is weaker at higher experience levels.	Supported

Note. H2 was supported in the basic and extended regression models, but the direct effect of subjective norms was marginally non-significant in the final moderated model including organisational innovation support as a control variable. Perceived behavioural control was significant only in the basic TPB model.

4.10 Chapter Summary

In summary, employees' intention to use AI tools at work was most strongly associated with attitudes toward AI and was also related to previous AI experience and organisational innovation support. Subjective norms were significant in the basic and extended models but marginally non-significant as a direct predictor in the final moderation model. The negative interaction between subjective norms and previous AI experience remained statistically significant after organisational innovation support was controlled. These findings describe statistical relationships within a cross-sectional sample and should not be interpreted as causal effects.

5 Chapter 5: Discussion

5.1 Overview of the Main Findings

The purpose of the present study was to examine statistical associations between employees' intention to use artificial intelligence tools in the workplace and attitudes toward AI tools, subjective norms, perceived behavioural control, previous experience with AI tools and organisational innovation support. The research model was mainly based on the Theory of Planned Behavior. Organisational innovation support was included as a contextual control variable in the final moderated regression model, rather than as a core TPB predictor or moderator.

Overall, the findings provide strong support for the relevance of the Theory of Planned Behavior in the context of workplace AI adoption. The basic TPB model, which included attitudes, subjective norms and perceived behavioural control, explained a substantial proportion of the variance in employees' intention to use AI tools. More specifically, the model accounted for 62.9% of the variance in intention, indicating that the three TPB predictors together offer a strong explanation of employees' willingness to use AI tools at work . This finding suggests that AI adoption in the workplace is not only a matter of technological availability, but also a behavioural process shaped by employees' evaluations, social environment and perceived capability.

Among the three TPB predictors, attitudes toward AI tools emerged as the strongest and most stable statistical predictor of intention. Subjective norms were positively associated with intention in the basic and extended models. However, their direct effect was marginally non-significant in the final moderation model that controlled for organisational innovation support. Perceived behavioural control was statistically significant in the basic TPB model, but its direct association with intention became non-significant after previous AI experience was added to the model.

The addition of previous AI experience was associated with an improvement in the explanatory power of the extended model. Previous AI experience was positively associated with intention in both the extended model and the final control-adjusted moderation model. This pattern is consistent with the view that familiarity and direct exposure may be relevant to employees' reported readiness to use AI, although the cross-sectional design does not establish a causal relationship.

The moderation analysis offered an additional and more nuanced insight. In the final model, which controlled for organisational innovation support, the interaction between subjective norms and previous AI experience was negative and statistically significant ($p = .013$). This indicates that the positive association between subjective norms and intention was weaker at higher levels of previous AI experience. The direct effect of subjective norms was marginally non-significant in that final model ($p = .074$), so the interaction should be interpreted as a conditional association rather than as a uniform direct effect.

Organisational innovation support was included as a contextual control variable in the final moderated regression model. It was positively associated with intention to use AI tools after attitudes, subjective norms, perceived behavioural control, previous AI experience and the interaction term were taken into account. However, it was not treated as a core TPB predictor or as a moderator. Its role should therefore be interpreted as contextual rather than central to the theoretical model.

5.2 The Role of Attitudes in Predicting Intention to Use AI Tools

The most important finding of the study concerns the role of attitudes toward AI tools. Attitudes were the strongest predictor of employees' intention to use AI tools in all regression models. In the basic TPB model, attitudes had a strong positive effect on intention. Even after previous AI experience and the interaction term were added, attitudes remained statistically significant and retained the largest standardised effect among the predictors .

This finding indicates that employees' personal evaluation of AI tools is central to their willingness to use them at work. Employees who perceive AI tools as useful, beneficial, efficient or valuable for their work are more likely to intend to integrate them into their professional activities. This is consistent with the Theory of Planned Behavior, according to which favourable attitudes toward a behaviour increase the likelihood of forming a strong intention to perform that behaviour (Ajzen, 1991). In the present study, using AI tools at work appears to be a behaviour that depends strongly on whether employees evaluate it positively.

The strong role of attitudes is also consistent with technology acceptance research. Davis (1989) argued that perceived usefulness is one of the most important determinants of technology acceptance, while Venkatesh et al. (2003) also highlighted performance expectancy as a central predictor of behavioural intention. In the context of AI tools, usefulness may refer to several perceived benefits, such as saving time, improving productivity, supporting decision-making, reducing repetitive work, generating ideas or helping employees manage information more effectively. If employees believe that AI tools can improve the way they work, they are more likely to develop positive attitudes and stronger intention.

The results also align with recent empirical studies on AI adoption. Srivastava et al. (2024) found that attitudes significantly predicted employees’ intention to use AI in the workplace, while Nguyen et al. (2026) showed that employees’ perceptions of AI, especially perceived usefulness and trust, shape affective attitudes and intention to use AI at work. The present findings support this line of research by showing that attitudes are not only statistically significant but also the most powerful predictor in the model.

The practical meaning of this finding is clear. Organisations that want to increase AI adoption should not assume that employees will use AI simply because tools are available. Employees need to understand the value of these tools for their own tasks. Positive attitudes are more likely to develop when AI is presented through concrete examples, realistic use cases and clear evidence of work-related benefits. For example, employees may become more willing to use AI when they see how it can help with drafting, summarising, analysing information, preparing reports or improving communication. General statements about innovation are less likely to be effective than practical demonstrations of how AI can support specific work activities.

At the same time, positive attitudes should not be built through unrealistic promises. If AI is presented as a perfect solution, employees may become disappointed when they encounter errors, limitations or generic outputs. A balanced approach is more appropriate. Employees should be encouraged to view AI as a useful support tool that can improve work when used critically and responsibly, not as a replacement for human judgement. In this sense, favourable attitudes should be based on realistic understanding rather than technological enthusiasm alone.

5.3 The Role of Subjective Norms

The findings indicate that subjective norms are relevant to employees' intention to use AI tools, although this relationship is not uniform across the regression models. Subjective norms were statistically significant in the basic TPB model and in the extended model with previous AI experience. In the final moderation model controlling for organisational innovation support, the direct effect was marginally non-significant ($p = .074$). This pattern suggests that the bivariate and model-specific role of social expectations should be distinguished from the conditional relationship captured by the interaction term.

This result supports the argument that AI adoption in the workplace is socially embedded. Employees do not decide whether to use AI tools only on the basis of their personal beliefs. They also consider whether important people in their professional environment approve of or encourage AI use. These important others may include colleagues, supervisors, managers, professional peers or people who influence their career development. When AI use is seen as acceptable, expected or supported by these actors, employees are more likely to form an intention to use AI tools.

The result is consistent with Ajzen's (1991) Theory of Planned Behavior, where subjective norms represent perceived social pressure to perform a behaviour. It is also consistent with technology acceptance research, especially the Unified Theory of Acceptance and Use of Technology, which identifies social influence as an important predictor of behavioural intention, particularly when a technology is new or organisationally visible (Venkatesh et al., 2003). Since AI tools are still relatively new in many workplaces, social cues may be especially important in helping employees decide whether their use is appropriate.

The importance of subjective norms is also understandable given the uncertainty surrounding AI. Employees may not always know whether AI use is permitted, whether it is considered professional, whether colleagues are using it or whether managers expect them to adopt it. In such contexts, employees may look to their work environment for signals. If colleagues discuss AI positively, if managers encourage responsible use or if AI tools are integrated into everyday workflows, employees may feel more confident that using AI is legitimate. Conversely, if the workplace culture is silent or sceptical toward AI, employees may hesitate even if they personally see potential benefits.

However, the findings of the moderation analysis show that the effect of subjective norms is not the same for all employees. Subjective norms were especially important for employees with lower previous AI experience. This means that social influence may matter most when employees have not yet formed their own strong evaluation of AI tools through direct use. When employees lack experience, they may depend more on colleagues and supervisors for guidance. When they have more experience, they may rely more on their own judgement.

This finding has practical significance. Organisations should recognise that social influence can be useful, especially during the early stages of AI adoption. Managers and experienced users can act as role models by demonstrating responsible and effective AI use. Peer learning can also help less experienced employees feel more comfortable. However, social influence should not take the form of pressure without support. Employees are more likely to respond positively when social expectations are accompanied by training, clear guidelines and opportunities to experiment safely.

5.4 The Role of Perceived Behavioural Control

Perceived behavioural control had a more complex role in the findings. In the basic TPB model, perceived behavioural control significantly predicted intention to use AI tools. This means that employees who felt more capable of using AI tools and believed that they had the necessary resources and control were more likely to intend to use them. This finding supports the TPB assumption that intention is stronger when individuals perceive that they can perform the behaviour (Ajzen, 1991).

However, when previous AI experience was added to the model, perceived behavioural control became non-significant. In the extended model, the effect of perceived behavioural control was no longer statistically significant, and this remained the case in the final moderation model . This means that the hypothesis concerning perceived behavioural control was supported in the basic TPB model, but not in the extended model that included previous AI experience.

This finding suggests that perceived behavioural control may partly overlap with previous AI experience. Employees who have already used AI tools may feel more capable of using them, while employees with little experience may feel less confident. When experience is included in the model, it may capture part of the variance that would otherwise be explained by perceived behavioural control. In other words, practical familiarity with AI tools may be a stronger or more concrete indicator of readiness than general perceived control.

Another possible explanation is that some employees may feel generally confident with technology but still be uncertain about AI-specific use. AI tools differ from traditional workplace software because their outputs require critical evaluation. Employees may know how to access and operate AI tools, but still feel unsure about when to trust them, how to check their accuracy or whether their use is acceptable in specific work situations. Therefore, perceived behavioural control may need to be understood in a more AI-specific way. General confidence may not be enough if employees do not have practical experience with AI outputs and their limitations.

The finding does not mean that perceived behavioural control is unimportant. Rather, it indicates that its predictive role becomes weaker when previous AI experience is considered. From a practical perspective, this means that organisations should not focus only on making employees feel capable in a general sense. They should also provide real opportunities for hands-on experience. Training, workshops, pilot projects and practical exercises may help employees move from abstract confidence to actual familiarity.

This result is also consistent with the idea that AI adoption requires both perceived and experiential capability. Employees may need to feel that they can use AI, but they also need actual exposure to understand how it works in practice. Therefore, perceived behavioural control remains relevant as part of the broader adoption process, even if it was not an independent predictor in the final model.

5.5 The Contribution of Previous AI Experience

Previous AI experience made a statistically significant contribution to the prediction of employees' intention to use AI tools. It was positively associated with intention in the extended model and remained statistically significant in the final moderation model controlling for organisational innovation support. These results describe an association between prior experience and reported intention and do not establish that prior experience causes later intention.

This finding highlights the importance of familiarity in AI adoption. Employees who have already used AI tools are likely to have a clearer understanding of their functions, benefits and limitations. They may know how to interact with AI tools, how to ask questions, how to interpret outputs and how to decide whether a result is useful. This practical knowledge can reduce uncertainty and make future use more likely.

Previous experience may also strengthen intention by increasing confidence. Employees who have used AI successfully may feel more capable of using it again. They may also perceive AI as less difficult or less intimidating. This is consistent with self-efficacy theory, according to which direct experience is one of the most important sources of confidence in performing a behaviour (Bandura, 1997). It is also consistent with technology adoption research, which shows that experience can influence later acceptance and use (Venkatesh et al., 2012).

The positive role of previous AI experience also suggests that AI adoption can develop gradually. Employees may start with simple uses, such as drafting, summarising or searching for ideas, and then move toward more complex applications as they gain confidence. This gradual learning process is important because AI tools often require experimentation. Unlike traditional software, where functions may be fixed and predictable, AI tools can produce different outputs depending on the user's input and the task context. Experience helps employees learn how to manage this variability.

However, the role of experience should not be interpreted as meaning that any AI use automatically leads to positive adoption. The quality of experience matters. Positive experiences may increase intention, while negative experiences may reduce it. If employees receive inaccurate, irrelevant or unreliable outputs, they may become more cautious. Therefore, organisations should support early experiences with AI carefully. Employees should be guided toward appropriate use cases and taught how to verify AI-generated outputs. This can help ensure that experience builds realistic confidence rather than blind reliance or unnecessary scepticism.

The findings of the present study suggest that experience is not only a background characteristic but also an active factor in AI adoption. It influences intention directly and also shapes the way employees respond to social influence, as shown by the moderation analysis. Therefore, future research and organisational practice should pay close attention to employees' level of AI experience when designing AI implementation strategies.

5.6 The Moderating Role of AI Experience

One of the key findings of the present study concerns the moderating role of previous AI experience in the relationship between subjective norms and employees' intention to use AI tools at work. The moderation analysis showed that the interaction between subjective norms and previous AI experience was negative and statistically significant. This indicates that the positive association between subjective norms and intention was weaker among employees with higher previous AI experience.

This finding can be interpreted through the role of uncertainty and direct experience. Employees with limited previous AI experience may not yet have a clear personal understanding of how useful, reliable or manageable AI tools are in their own work. In this context, their intention to use AI tools appears to be more strongly related to social signals from colleagues, supervisors and managers. When employees have little direct experience with AI, perceived social approval may be more relevant for their intention because it provides guidance about whether AI use is appropriate, acceptable and professionally useful.

By contrast, employees with higher previous AI experience may have already formed a more personal evaluation of AI tools through direct interaction with them. These employees are likely to have clearer views about the usefulness, limitations and risks of AI tools in relation to their own work tasks. For this reason, their intention to use AI appears to be less strongly related to subjective norms. This does not mean that social influence becomes irrelevant, but rather that its statistical association with intention is weaker among employees with higher AI experience.

The negative interaction coefficient supports this interpretation. After organisational innovation support was included as a control variable, the association between subjective norms and intention was weaker at higher levels of previous AI experience. Because the present design is cross-sectional, this pattern should be understood as a conditional statistical association rather than as evidence that experience causally changes employees' response to social norms.

This finding is theoretically meaningful because it extends the Theory of Planned Behavior in the context of workplace AI adoption. The TPB suggests that subjective norms are associated with behavioural intention, but the present findings show that this association may depend on employees' previous experience with the technology. In the case of AI tools, social influence appears to be more strongly related to intention when employees have limited direct experience and less strongly related to intention when employees have already interacted with AI tools.

From a practical perspective, this result suggests that organisations may need different AI adoption strategies for employees with different levels of AI experience. Employees with limited AI experience may benefit more from visible support, encouragement and practical examples from colleagues and supervisors. For these employees, social cues from the workplace may be especially relevant because they can reduce uncertainty and make AI use appear more acceptable and manageable. Employees with higher AI experience, on the other hand, may benefit more from advanced guidance, clear policies and opportunities to apply AI tools in more specialised or complex work tasks.

Since the study followed a cross-sectional design, this moderation finding should not be interpreted causally. The results do not prove that previous AI experience reduces the influence of subjective norms. Rather, they show that the statistical relationship between subjective norms and intention differs depending on the level of previous AI experience. Overall, the findings suggest that previous AI experience is an important condition under which social influence is more or less strongly related to employees' intention to use AI tools at work.

5.7 The Role of Organisational Innovation Support

Organisational innovation support was included in the study as a contextual control variable. It refers to the extent to which employees perceive that their organisation encourages new ideas, supports technological learning and provides an environment open to innovation. In the measurement model, innovation support was included as a separate construct, and the CFA results showed that its indicators loaded on the expected factor. The standardised loadings for the innovation support items ranged from acceptable to strong, indicating that the items captured the construct reasonably well.

The descriptive statistics showed that organisational innovation support had a mean score of 3.228, suggesting a moderate level of perceived innovation support in the sample. In the final moderated regression model, innovation support was positively associated with intention to use AI tools ($B = .152$, $beta = .167$, $p = .019$) after the main TPB variables, previous AI experience and the interaction term were taken into account.

Organisational innovation support was not treated as a central TPB predictor or as a moderator. Instead, its inclusion as a control variable made it possible to take account of the organisational context while retaining the main focus on the TPB variables, previous AI experience and the interaction between subjective norms and previous AI experience. The significant control-variable coefficient indicates a contextual association with intention, not a new causal pathway within the TPB model.

The present cross-sectional data cannot determine whether organisational innovation support operates through direct or indirect pathways. It may be related to attitudes, perceived behavioural control or subjective norms, but such mechanisms require longitudinal or experimental research. The current result only indicates that employees who reported stronger innovation support also reported stronger intention after the other measured variables were statistically controlled.

This interpretation is consistent with organisational readiness research, which suggests that technology adoption is related not only to individual willingness but also to organisational capabilities and support. Hradecky et al. (2022) argue that AI readiness involves strategy, resources, skills and organisational context. Similarly, organisational behaviour research indicates that innovation is more likely to be reported in environments where employees perceive support for new ideas and experimentation (Amabile et al., 1996; Scott & Bruce, 1994).

For the present study, organisational innovation support should therefore be interpreted as a contextual control variable that was positively associated with intention, rather than as a confirmed core determinant within the TPB model. Future research could assess its role more directly as a predictor, moderator or antecedent of attitudes and perceived behavioural control using designs that can test temporal ordering.

5.8 Comparison with Previous Literature

The findings of the present study are broadly consistent with previous literature on technology acceptance, the Theory of Planned Behavior and AI adoption. The strong effect of attitudes on intention supports Ajzen’s (1991) theory and is also consistent with Davis’s (1989) Technology Acceptance Model, where favourable evaluations of technology, especially perceived usefulness, are central to adoption. The result also aligns with recent AI adoption studies showing that positive perceptions and affective attitudes toward AI influence employees’ intention to use AI at work (Nguyen et al., 2026; Srivastava et al., 2024).

The role of subjective norms is partly consistent with prior research. Subjective norms were statistically significant in the basic and extended models, which is consistent with the TPB and research identifying social influence as relevant to technology acceptance (Srivastava et al., 2024; Venkatesh et al., 2003). However, their direct effect was marginally non-significant in the final moderation model controlling for organisational innovation support. This qualification suggests that the role of social influence should be interpreted in relation to employees' previous AI experience and the organisational context.

The results concerning perceived behavioural control are partly consistent with the literature. In the basic TPB model, perceived behavioural control significantly predicted intention, which supports Ajzen’s (1991) theoretical assumptions and previous AI adoption research. However, its effect became non-significant after previous AI experience was added. This differs from some studies where perceived behavioural control remains a strong predictor. The difference may be explained by the specific nature of AI tools. In this study, direct experience with AI may have captured a more concrete aspect of capability than perceived control alone.

The positive effect of previous AI experience is consistent with technology adoption literature, which suggests that experience can shape beliefs, confidence and future use (Venkatesh et al., 2012). It also fits the idea that AI familiarity reduces uncertainty. Employees who have used AI tools before may be more able to judge their value and may feel more comfortable using them again. This finding adds to the literature by showing that previous AI experience is not only relevant as a background characteristic but also as a direct predictor of intention.

The moderation finding adds a particularly valuable contribution. Previous research has shown that social influence can be moderated by experience in technology adoption (Venkatesh et al., 2003, 2012). The present study confirms this logic in the specific context of AI tools. The finding that subjective norms matter more for employees with low AI experience suggests that social influence is especially important when employees are uncertain or unfamiliar with AI. This provides a more nuanced understanding of AI adoption than a model that only examines direct effects.

The findings also connect with research on AI trust and technostress. Glikson and Woolley (2020) argue that trust in AI is shaped by reliability, transparency and task context. Although trust was not measured directly in the present study, attitudes and previous experience may partly reflect trust-related evaluations. Similarly, Chang et al. (2024) showed that AI-related stress can either promote or hinder adoption depending on whether it is experienced as a challenge or a hindrance. The present finding that experience increases intention may suggest that familiarity helps employees experience AI as more manageable.

Overall, the study supports the general conclusion that AI adoption at work is a multidimensional process. It is influenced by personal evaluations, social expectations, perceived capability and direct experience. At the same time, the study shows that the relative importance of these factors may change depending on employees' level of AI experience.

5.9 Theoretical Implications

The present study has several theoretical implications. First, it confirms the usefulness of the Theory of Planned Behavior as a framework for studying employees' intention to use AI tools in the workplace. The basic TPB model explained a large proportion of the variance in intention, showing that attitudes, subjective norms and perceived behavioural control remain relevant in the context of emerging workplace technologies.

Second, the study shows that attitudes may be the most important TPB predictor in AI adoption. This suggests that employees' personal evaluation of AI tools is central when the behaviour involves new and potentially transformative technologies. The strong role of attitudes indicates that future research should examine in more detail the specific beliefs that form attitudes toward AI, such as perceived usefulness, trust, perceived risk, ethical concerns, job security and perceived compatibility with work tasks.

Third, the findings suggest that perceived behavioural control may need to be examined carefully in AI adoption studies. Its effect was significant in the basic model but not in the extended model with previous AI experience. This implies that perceived capability and actual experience may be closely related. Future research could distinguish between general digital self-efficacy, AI-specific self-efficacy, access to resources and previous hands-on experience. Such distinctions may improve the explanatory power of AI adoption models.

Fourth, the study contributes to the literature by highlighting the role of previous AI experience. Experience was not only a direct predictor of intention but also a moderator of the relationship between subjective norms and intention. This suggests that AI adoption models should not treat all employees as equally unfamiliar with AI. Instead, employees' level of experience should be considered because it changes how they respond to social influence.

Fifth, the moderation finding extends the TPB in a meaningful way. It shows that the relationship between subjective norms and intention depends on previous AI experience. This supports the idea that social influence is stronger when individuals face uncertainty and weaker when they have direct experience. In the context of AI, this is particularly important because familiarity with AI tools is uneven across employees and organisations.

Finally, the inclusion of organisational innovation support as a control variable points to the value of models that combine individual and organisational perspectives. In the final moderation model, innovation support was positively associated with intention, while the principal theoretical focus remained on the TPB variables and previous AI experience. Future research could test more complex models in which organisational support is temporally related to attitudes, perceived behavioural control or actual AI use.

5.10 Practical Implications for Organisations and Managers

The findings of the study have several practical implications for organisations and managers seeking to support AI adoption in the workplace. First, because attitudes were the strongest predictor of intention, organisations should focus on helping employees develop realistic and positive evaluations of AI tools. This can be achieved through practical demonstrations, examples of successful use, task-specific training and open discussion of both benefits and limitations. Employees are more likely to intend to use AI when they understand how it can help them in their actual work.

Second, managers should not rely only on providing access to AI tools. Access is necessary, but it is not sufficient. Employees need to see AI as useful, relevant and trustworthy. Organisations should therefore communicate clearly what AI tools are for, which tasks they can support and how employees should evaluate AI-generated outputs. AI should be presented as a tool that supports human judgement rather than replaces it.

Third, the pattern for subjective norms suggests that managers and colleagues can provide relevant social cues about responsible AI use, particularly for less experienced employees. Because the final model showed a marginally non-significant direct effect of subjective norms, recommendations concerning social influence should be treated as informed by the overall pattern of results rather than as evidence of a stable direct causal effect. Leaders can model responsible AI use, encourage discussion and make organisational expectations clear.

Fourth, because subjective norms were most important for employees with low AI experience, organisations should pay special attention to beginners. Employees with little experience may need reassurance, examples and social encouragement before they feel ready to use AI. Managers should create low-risk opportunities for these employees to experiment with AI tools. This may include workshops, guided practice, internal use cases and mentoring by more experienced users.

Fifth, the positive effect of previous AI experience suggests that hands-on learning is essential. Organisations should create opportunities for employees to gain direct experience with AI tools in safe and controlled conditions. Training should not be limited to theoretical presentations. It should include practical exercises, real work scenarios and guidance on how to check outputs, avoid errors and protect confidential information.

Sixth, the non-significant role of perceived behavioural control in the extended model suggests that general confidence may not be enough. Employees need concrete experience and clear guidance. Therefore, organisations should provide approved AI tools, written policies, ethical guidelines and technical support. Employees should know which tools they are allowed to use, what data they can input and how AI-generated outputs should be reviewed.

Seventh, organisational innovation support deserves attention. In the final model, it was positively associated with intention when entered as a contextual control variable. This result does not establish that increasing innovation support will cause greater AI use, but it supports the practical value of examining whether organisations provide resources, clear guidance and opportunities for responsible experimentation.

Finally, managers should recognise that AI adoption is not the same for all employees. Employees differ in attitudes, experience, confidence and sensitivity to social influence. For this reason, AI implementation strategies should be flexible. Less experienced employees may need more social support and basic training, while more experienced employees may need advanced guidance, ethical frameworks and opportunities to apply AI in more complex tasks. A successful AI adoption strategy should therefore combine technology, training, leadership, peer support and responsible governance.

Overall, the findings suggest that AI adoption in the workplace should be managed as a human and organisational change process, not merely as a technological upgrade. Employees' intention to use AI tools depends on how they evaluate AI, how their workplace responds to AI, how much experience they have and whether they feel supported in using it responsibly. Organisations that understand these factors are more likely to achieve meaningful, ethical and sustainable AI adoption.

6 Chapter 6: Conclusions

The first main conclusion is that employees' attitudes toward AI tools were the strongest statistical predictor of their reported intention to use them at work. Across the regression models, attitudes remained the strongest and most stable predictor. This result indicates a strong positive association between favourable evaluations of AI tools and intention within the present sample; it does not establish that attitudes cause intention.

The second conclusion is that subjective norms were relevant to workplace AI adoption, but their direct association with intention differed across models. They were statistically significant in the basic and extended models, whereas their direct effect was marginally non-significant in the final moderated model controlling for organisational innovation support. The negative interaction with previous AI experience remained statistically significant, indicating that the association between subjective norms and intention was weaker at higher levels of prior experience.

The third conclusion concerns perceived behavioural control. In the basic TPB model, perceived behavioural control statistically predicted intention. However, after previous AI

experience was added, its association with intention was no longer statistically significant. This pattern may indicate overlap between perceived capability and prior experience, but the cross-sectional data cannot establish the direction of that relationship.
The fourth conclusion is that previous AI experience was positively associated with employees' intention to use AI tools. Employees reporting more experience also reported stronger intention in the extended and final models. This association is consistent with the relevance of familiarity, although it should not be interpreted as proof that experience causes later intention.
The fifth and perhaps most nuanced conclusion concerns the moderating role of previous AI experience. In the final model controlling for organisational innovation support, the negative and statistically significant interaction indicated that the association between subjective norms and intention was weaker at higher levels of previous AI experience. This result is consistent with the interpretation that social cues may be more relevant for employees with limited experience, but it does not prove that experience reduces social influence.
The sixth conclusion concerns organisational innovation support. It was included as a contextual control variable in the final regression model and was positively associated with intention to use AI tools. It was not treated as a core component of the TPB model or as a moderator. This result highlights the relevance of organisational context, while not establishing a causal effect of innovation support on AI-use intention.
Overall, the study indicates that employees' intention to use AI tools at work is associated with personal evaluations, previous AI experience, organisational innovation support and, conditionally, subjective norms. Because all variables were measured at one point in time, the findings should be interpreted as statistical associations rather than causal relationships. Longitudinal and experimental studies are needed to examine temporal ordering and causal mechanisms.

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