Understanding Workplace AI Use: A Mixed-Method Study at Nedap

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Abstract

As generative artificial intelligence becomes increasingly embedded in everyday work practices, organizations face the challenge of understanding not only whether employees adopt AI tools, but how AI use translates into meaningful value in practice. This study examines workplace AI use at Nedap through a mixed-method design that moves beyond adoption metrics to explain why employees choose to use AI, how they integrate it into daily work, and how AI-related value can be better supported through interaction design. Drawing on the Unified Theory of Acceptance and Use of Technology and its extensions, a quantitative survey (N = 97) examined determinants of employees' intention to use AI tools. Principal component analysis revealed that the resulting factor structure aligned more closely with the Theory of Planned Behavior, with Trust emerging as a critical AI-specific extension, than the original proposed model. Partial least squares structural equation modeling revealed that intention to use AI is primarily driven by attitude toward AI and trust (in both AI systems and organizational governance), while subjective norms and perceived behavioral control played no significant role. Complementing these findings, qualitative interviews (N = 7) explored how employees enact AI use in everyday work. The interviews show that AI is predominantly used as an assistive and augmentative tool to reduce friction, support learning, and provide starting points in situations of uncertainty, while human judgment and responsibility remain central. These insights help explain the significance of attitude and trust in the survey results: employees value AI not because it is easy to use or socially expected, but because it can support autonomy and sense-making when its limitations are actively managed. Building on the combined findings, a design-based intervention, the *Prompt Coach*, was developed to address recurring interaction challenges related to unclear prompting and unreliable outputs. Together, the study demonstrates that effective workplace AI use depends less on enforcing adoption and more on fostering positive attitudes, calibrated trust, and supportive interaction design that enables employees to translate AI use into sustained organizational and individual value.

Introduction

Generative Artificial Intelligence (GenAI) is rapidly becoming embedded in the modern workplace and is used across roles from software development to marketing and human resources (Aguinis et al., 2024; Ferraro et al., 2024; Grewal et al., 2024; Mozannar et al., 2024; Peng et al., 2023). As AI tools become part of everyday workflows, they are not only shaping individual productivity but also transforming how teams collaborate, particularly in organizations where professionals with diverse skill sets must work together (Tummala et al., 2025). Yet, despite these developments, many organizations lack a clear understanding of how employees actually use AI, whether such use aligns with organizational goals, and what tangible benefits result from adoption (Schmutz et al., 2024). This tension highlights a critical gap between measuring AI use and understanding how AI creates value at both the organizational and individual levels, underscoring the need to complement adoption-focused frameworks with empirical insights into actual workplace use.

Nedap N.V., founded in 1929, provides a compelling case for examining these questions. As a multinational technology company, Nedap operates in domains such as healthcare, livestock, retail, and security management. Guided by its philosophy of "Technology for Life," the company has steadily transitioned from hardware roots to becoming a software- and SaaS (Software-as-a-Service)-driven enterprise that integrates digital technologies, including IoT (Internet of Things), RFID (Radio Frequency Identification), and increasingly, artificial intelligence ("Technology for life - Nedap," n.d.). In healthcare, Nedap supports over 1,900 providers in the Netherlands by improving accessibility and efficiency of care, while in retail and livestock, it delivers solutions that optimize supply chains and animal welfare. This long-standing emphasis on integrating human-centered design with technological innovation provides a rich organizational context for examining how AI is adopted, interpreted, and used in practice across different domains and roles.

Despite growing interest in workplace AI, existing research remains largely focused on adoption intentions rather than on how AI is actually used in everyday work and how such use translates into value (Chowdhury et al., 2022; Jain et al., 2022). Adoption-oriented frameworks are well-suited to explaining individual intentions and determinants of initial use, but they offer limited insight into how AI becomes embedded in situated workplace practices or how usage relates to organizational and individual outcomes (Fetaji, 2023; Jain et al., 2022; Tamilmani et al., 2021; Venkatesh, 2022; Venkatesh et al., 2003). As a result, there is a theoretical gap between measuring AI adoption and understanding AI use as a socio-technical practice that creates (or fails to create) value.

Nedap serves as an illustrative empirical case for examining this gap. The organization has implemented systems to monitor AI adoption across its workforce, enabling the tracking of which employees use AI tools, which products they use, and how frequently they engage with them. While such metrics provide visibility into adoption patterns, they do not capture how AI is used in practice, whether employees use these tools effectively, or what value AI use generates for both the organization and its staff. This disconnect between measurable adoption and meaningful outcomes highlights the need to complement adoption-focused models with empirical insights into actual workplace AI use.

To address this challenge, the present study has two main objectives. First, it seeks to understand AI adoption and usage at Nedap through the lens of the Unified Theory of Acceptance and Use of Technology (UTAUT). UTAUT is a well-established framework for explaining technology acceptance in organizational contexts, positing that users' adoption and use of new technologies are primarily influenced by performance expectancy, effort expectancy, social influence, facilitating conditions, and more (Venkatesh et al., 2003, 2012). Building on this framework, the study adopts a mixed-method approach that combines quantitative survey data with qualitative interviews. The survey component draws on UTAUT and its extensions to identify key factors associated with employees' adoption and use of AI tools, as well as their perceived outcomes. However, given that UTAUT primarily captures individual intentions and self-reported determinants of use, it offers limited insight into how AI is actually integrated into everyday work practices. To address this limitation, qualitative interviews are employed to explore how employees make sense of AI, how they use it in specific work contexts, and how they experience its benefits and challenges in practice. Second, it aims to investigate negative AI experiences and, through a design-case intervention, prototype support mechanisms that could improve employee–AI interactions and increase the value of AI use in practice. Together, these approaches not only provide insights into adoption but also generate actionable interventions to enhance the organizational benefits of AI adoption.

Accordingly, the main research questions guiding this study are:

- **RQ1: What factors influence employees' adoption and use of AI tools, as explained by the UTAUT framework and its extensions?**
- **RQ2: How do employees currently use AI in their daily work, and what outcomes do they associate with this usage?**
- **RQ3: How can a design-based intervention address the identified challenges and support**

more effective and beneficial AI use across the organization?

Background And Literature Review

What is AI, GenAI, and Its Related Technologies?

Artificial Intelligence (AI) broadly refers to computational systems designed to perform tasks that traditionally require human intelligence, such as reasoning, learning, and problem-solving. Within AI, machine learning (ML), particularly deep learning, has enabled systems to improve their performance by identifying patterns in large datasets rather than relying on static, rule-based programming (Haenlein & Kaplan, 2019; Hagos et al., 2024). These developments form the foundation for more advanced applications of AI that go beyond prediction or classification to the creation of new content.

Generative Artificial Intelligence (GenAI) represents such an advancement. Unlike conventional AI, which is often limited to recognizing inputs or executing predefined processes, GenAI systems can generate (original) outputs, including text, images, audio, and code (Sengar et al., 2025). This generative capacity is enabled by models trained on broad and diverse data, allowing them to simulate creativity and support human activities in knowledge work, communication, and innovation. A central subset of GenAI is Large Language Models (LLMs), which specialize in understanding and generating human language (Hagos et al., 2024). LLMs, such as GPT-3 and its successors, are trained on massive collections of text and employ transformer-based architectures, allowing them to produce coherent, contextually appropriate responses, summarize information, and act as conversational agents.

These capabilities are becoming increasingly integrated with related technologies such as automation and AI Agents. Traditional automation systems focused on repetitive, structured tasks, but when combined with GenAI and LLMs, automation extends into more complex and adaptive domains, such as drafting documents, coding, or generating design ideas (Dinçkal, 2024; Thakur et al., 2025). AI agents build on this foundation by introducing autonomy, enabling them to perceive environments, plan actions, and execute tasks in an ongoing, adaptive manner. While LLMs often provide the core reasoning and language-generation, AI agents integrate additional functionalities such as memory, decision-making, and the use of external tools (Xi et al., 2025). Together, these technologies show how systems have evolved from narrow, rule-based to generative and adaptive, reshaping individual productivity, collaboration, and organizational processes.

General AI Adoption in Workplace

In recent years, generative AI has been rapidly adopted across a range of job functions. Once the domain of technical experts, GenAI tools are now widely used by non-technical staff as well. A recent global survey found that 78% of respondents ($N = 1491$) use GenAI in at least one function, with top applications ranging from software development (code generation) to marketing and customer services (content creation) (Singla et al., 2025). This trend is especially pronounced in technical domains, but is increasingly extending to business professionals who now incorporate AI tools into their daily workflows. Developers, for example, use coding assistants such as GitHub Copilot for programming tasks, while professionals in marketing, human resources, and other roles employ GenAI to draft content, brainstorm ideas, and conduct text analyses. Other recent surveys confirm this broad adoption: about 76% of developers currently use or intend to adopt AI coding tools ("AI | 2024 Stack Overflow Developer Survey," n.d.), and nearly 90% of marketing professionals have used GenAI (Cashion & OBrien, 2024). These tools are often associated with enhancing productivity and creativity, and 85% of marketers report moderate to significant improvement in their productivity by using GenAI, while 88% of developers report the same effect (Cashion & OBrien, 2024; Kalliamvakou, 2022; Ziegler et al., 2022).

Benefits of AI Use in the Workplace

Many studies have shown that adopting AI can benefit both employees and organizations. One of the most common advantages is improved productivity. Studies in different fields have found that AI support helps people complete tasks more quickly, often with the same or better quality than without AI. For instance, a study found that developers using AI code generators completed programming tasks significantly faster than those without AI, with comparable or even improved code quality (Peng et al., 2023). Likewise, non-technical professionals using AI assistants are able to produce written materials and resolve issues more efficiently and effectively than individuals who work alone (Brynjolfsson et al., 2025; Noy & Zhang, 2023). Furthermore, Dell'Acqua et al. (2025) found that an individual supported by a GenAI could match the performance of a traditional two-person team on certain tasks, such as ideation, strategy development, or solving business problems. These findings underscore AI's potential to strengthen human work by offering quick access to knowledge, creativity, and speed when needed.

Beyond raw productivity, AI can also improve quality and innovation by reducing repetitive tasks and freeing employees for creative and complex work (Dell'Acqua et al., 2023; Noy & Zhang, 2023). In creative and knowledge-based roles, AI is often compared to a "collaborator" that can inspire new ideas and broaden the range of possible solutions (Sedkaoui & Benaichouba, 2024). Dell'Acqua et al. (2025) pointed out that teams using GenAI during product development brainstorming produced more balanced ideas across both technical and non-technical areas, while teams without AI tended to remain within their own areas of expertise. This finding shows that AI can make cross-functional team work more effective by reducing entry barriers and allowing people to explore tasks beyond their usual roles. The same study also noted that AI integration tends to generate positive emotional responses, such as greater excitement, enthusiasm, and reduced anxiety, indicating that effective adoption should help workers recognize and embrace these benefits (Dell'Acqua et al., 2025).

Another commonly noted advantage of AI in the workplace is its contribution to skill building and learning. Although studies in this area are still emerging, some suggest that using AI can support employees in gaining new knowledge or strengthening specific skills. For example, using AI and related technologies might teach employees better ways to problem-solve (through AI suggestions) or improve their digital skills (as they learn to prompt and refine AI outputs). Chowdhury et al. (2022) suggests that when managed well, collaboration with AI can strengthen both organizational knowledge sharing and individual abilities by combining human intuition with machine intelligence. AI tools often contain expert knowledge (Peralta et al., 2025). When employees use these tools, they may learn indirectly from the AI's suggestions and feedback. One previous study supports this idea: Noy and Zhang (2023) found that workers using AI as writing assistants improved the quality of their reports; they also found that AI can support users with weaker initial skills, helping them to improve more quickly. However, gaining real learning benefits likely depends on using AI reflectively and treating it as a learning partner rather than just a shortcut (Chowdhury et al., 2022; Noy & Zhang, 2023).

Despite the generally positive findings reported in prior research, it is important to acknowledge that the benefits if AI use in the workplace are not universal and often depend strongly on task characteristics, user expertise, and organizational context (Brynjolfsson et al., 2025; Dell'Acqua et al., 2023). Many of the studies rely on controlled laboratory experiments or short-term field experiments that focus on narrowly defined tasks, such as writing assignments, programming challenges, or ideation exercises (Noy & Zhang, 2023; Peng et al., 2023). While such designs allow for strong causal inference, they may overestimate AI's effectiveness in real-world settings, where tasks are more complex, interdependent, and embedded in broader organizational workflows (Brynjolfsson et al., 2025; Chowdhury et al., 2022; Schmutz et al., 2024). As a result, gains observed under experimental conditions may not translate directly into sustained improvements in everyday work practices (Venkatesh, 2022). Existing studies also suggest that AI does not benefit all users equally. Prior research indicates that less-experienced workers may benefit more from AI assistance than experts, while highly skilled users may experience smaller gains or even constraints on their autonomy and judgment (Brynjolfsson et al., 2025; Dell'Acqua et al., 2023). The value of AI use may vary across organizational contexts depending on factors such as governance structures, support mechanisms, trust in AI systems, and alignment with organizational goals (Afroogh et al., 2024; Chowdhury et al., 2022; Venkatesh, 2022). As a result, treating reported benefits as generalizable outcomes risks oversimplifying how AI creates value in practice.

Taken together, these limitations indicate that existing evidence provides an incomplete picture of how AI contributes to learning, productivity, and skill development in organizational contexts. Rather than treating experimental findings as universally generalizable, there is a need for research that examines AI use as it unfolds in real work environments, accounting for contextual factors, user diversity, and everyday challenges. This study addresses this gap by combining quantitative measures with qualitative insights from a case study at Nedap, allowing both perceived outcomes and experienced difficulties of AI use to be examined in context. Such a mixed-method approach enables a more nuanced understanding of when, how, and for whom AI use delivers meaningful benefits beyond controlled experimental settings.

Challenges and Barriers in Workplace AI Integration

While the promise of AI in the workplace is high, research has also highlighted numerous challenges, barriers, and unintended consequences that can accompany AI adoption. One fundamental issue is trust; both a lack of trust in AI systems and in the organizational governance surrounding them are critical barriers to productive use. People are often hesitant to use AI after seeing it makes mistakes (algorithm aversion), even when it generally outperforms human alternatives (Dietvorst et al., 2015). In the workplace, this issue is intensified by the "black box" nature of many systems, which makes their decisions difficult to understand (Afroogh et al., 2024). When employees do not understand how AI works or recall cases of widely publicized AI failures, their skepticism can lead them to reject or ignore AI recommendations (Thiebes et al., 2021). Yet, trust does not depend only on the model itself. Institution-based trust and confidence, rooted in organizational policies, procedures, and safeguards, could also influence employees' adoption (McKnight et al., 2002). Measures such as clear rules for responsible use, transparency mechanisms, and independent audit and accountability practices can make AI outputs seem more legitimate and less risky (Raji et al., 2020). Similarly, visible adherence to privacy and accountability regulations can strengthen perceptions of fairness and safety (Wachter et al., 2017). Without governance, employee trust remains fragile, causing highly accurate systems to end up underused.

Another barrier is the poor usability and weak workflow integration of AI tools. If an AI system is difficult to operate, such as requiring complicated prompts or producing outputs that are hard to interpret, employees may abandon it despite its potential value (Jain et al., 2022). Studies on technology adoption consistently show that ease of use is a key driver of acceptance, and AI follows the same pattern. Workers are more likely to adopt AI when it fits seamlessly into their existing processes and interfaces (Jain et al., 2022). In contrast, when AI and related technologies are poorly integrated, such as by creating extra work through frequent configurations, it often leads to frustration and resistance (Golgeci et al., 2025). In short, any mismatch between AI tools and employees' workflows or cognitive load can undermine their effective use.

The third barrier arises when AI is introduced into team workflows, as it can create friction around roles and communication. When an "AI teammate" is added, team members may be uncertain about how to divide tasks or how much to rely on the AI, which can cause role confusion. Research on human-AI collaboration shows that mixed teams often perform worse than all-human teams unless the AI's role is clearly defined and coordination is actively managed (Schmutz et al., 2024). For instance, adding an AI agent without clear communication protocols has been shown to cause coordination breakdowns and reduce shared understanding. Without thoughtful integration, AI can disrupt team processes by creating misunderstandings, duplicated work, or over-reliance, which ultimately lowers performance (Demir et al., 2017; Johnson et al., 2023; McNeese et al., 2021). These findings stress the importance of role clarity and team-level adaptation when implementing AI in collaborative settings.

In summary, the three identified barriers highlight that integrating AI in the workplace is as much a human and organizational challenge as it is a technical one. Simply introducing advanced AI tools is insufficient; organizations must actively foster user trust, ensure that AI systems are usable and well integrated into existing workflows, and clearly define AI's role within teams. While prior research has documented these challenges conceptually, less is known about how they manifest in everyday work practices and how organizations can effectively address them in situations. Building on the challenges identified in the literature, this study therefore examines how barriers to AI use emerge in practice at Nedap and explores ways to mitigate them through targeted, design-oriented interventions. By focusing on employees' concrete experiences with AI-related difficulties and organizational responses to these challenges, the study aims to generate actionable insights into improving AI adoption and use in real-world organizational settings.

Nedap and Its Current Situation on AI Adoption

Nedap has established itself as an organization at the forefront of experimenting with and adopting AI tools in the workplace. In order to obtain metrics on AI usage, Nedap has already implemented systems that allow the tracking of AI use across the company. Through monitoring mechanisms such as email registration and usage credits, the company possesses detailed quantitative data on who uses AI, what products are being used, and how frequently these tools are engaged. This infrastructure provides Nedap with visibility into adoption patterns, setting a strong foundation for understanding AI integration within its organizational ecosystem.

However, the quality and effectiveness of AI use remain largely unknown. Specifically, the company lacks clarity on how employees are engaging with AI in their day-to-day work practices and whether these interactions align with "best use" cases that maximize value. As adoption alone does not guarantee positive outcomes (Schmutz et al., 2024; Venkatesh et al., 2003), this knowledge is crucial for the company. Employees may adopt AI superficially, use it inefficiently, or even develop reliance patterns that undermine skill development and autonomy.

This situation highlights a key challenge: current monitoring systems show basic statistics about AI use but do not explain how or why employees engage with these tools. For Nedap, the issue is not whether adoption happens, but whether adoption leads to valuable outcomes for both employees and the organization. To address this, a combined approach is needed: structured evaluation through surveys based on models such as UTAUT to shed light on the usage determinants, and exploratory research into employees' experiences of difficulties or failures with AI. By doing so, Nedap aims to move from simply "knowing that employees use AI" to "understanding whether AI use genuinely benefits people and the organization."

Theoretical Framework

The Unified Theory of Acceptance and Use of Technology (UTAUT), developed by Venkatesh et al. (2003), is a key framework for analyzing technology adoption in organizations. It synthesizes earlier technology acceptance models into four core determinants of usage: performance expectancy, effort expectancy, social influence, and facilitating conditions. Later extensions of the model, known as UTAUT2, adapted it for consumer and voluntary contexts by adding constructs such as hedonic motivation, habit, and price value (Venkatesh et al., 2012). While price is less relevant in organizational contexts such as Nedap, enjoyment and habit may play important roles. Employees who find AI tools engaging are more likely to continue using them, and once AI use becomes routine, continued adoption is more likely. UTAUT and UTAUT2 have proven to be highly robust in explaining technology adoption intentions (Su et al., 2025; Venkatesh et al., 2003, 2012). Recent AI-specific studies continue to confirm the relevance of these factors, showing that usefulness, ease of use, social endorsement, and organizational support positively predict actual AI tool use (Jain et al., 2022; Venkatesh, 2022). However, as mentioned above, adopting AI in the workplace may involve additional considerations of trust. Employees must trust both the AI systems and the organizational context in which those systems are implemented. Therefore, trust in AI (addressing algorithmic aversion) and organizational trust were introduced as additional predictors in our extended model. The following sections discuss each predictor in our extended UTAUT model and formulate hypotheses regarding their impact on AI and related technologies adoption and use in the workplace.

Performance Expectancy (PE)

Performance expectancy refers to "the degree to which an individual believes that using the system will help him or her to attain gains in job performance" (Venkatesh et al., 2003). In other words, the more AI and related technologies are expected to improve efficiency or effectiveness at work, the more likely employees are to use them. Performance expectancy has consistently been found to be one of the strongest predictors of technology adoption in organizational settings (Dwivedi et al., 2019; Jain et al., 2022; Khechine et al., 2016; Su et al., 2025). This pattern holds true for AI applications as well; prior studies on AI and related technologies show that performance expectancy significantly impacts the intention to use AI (Andrews et al., 2021; Chatterjee et al., 2023; Jain et al., 2022; Su et al., 2025).

However, the positive influence of performance expectancy is not universal (Brynjolfsson et al., 2025; Khechine et al., 2016; Tamilmani et al., 2021). Prior researches suggest that perceived performance gains from AI may weaken when benefits are marginal, when AI outputs require substantial verification, or when recommendations conflict with employees' professional judgment and autonomy (Brynjolfsson et al., 2025; Chowdhury et al., 2022; Jain et al., 2022). In complex or creative tasks, particularly among highly experienced users, AI support may be perceived as constraining rather than enabling, thereby reducing its perceived usefulness (Brynjolfsson et al., 2025). Moreover, early expectations of productivity gains may decrease over time if AI systems do not perform reliably in real-world work settings (Schmutz et al., 2024). These findings suggest that the impact of performance expectancy on AI adoption depends on task characteristics, user expertise, and consistent system performance. Nevertheless, when employees perceive that AI tools meaningfully support their work and enhance outcomes without undermining professional autonomy, performance expectancy is likely to act as a strong driver of adoption. Therefore, I posit that performance expectancy positively influences Nedap employees' intention to adopt and use AI and related technologies.

Effort Expectancy (EE)

Effort expectancy is defined as "the degree of ease associated with use of the system" (Venkatesh et al., 2003). User-friendly technologies that require minimal effort to learn or operate are more readily adopted by users. In the context of workplace AI tools, effort expectancy means that if an AI application, such as an internal chatbot or automation software, is intuitive and not overly complex, employees will be more likely to try it. Empirical research supports the importance of effort expectancy in AI acceptance (Chatterjee et al., 2023; Jain et al., 2022; Su et al., 2025). Even when its effect is modest compared to performance gains, a positive ease of use can still facilitate adoption (Su et al., 2025). Employees tend to resist tools that are seen as difficult or cumbersome; therefore, ensuring that an AI system is accessible (through good design training and support) can remove barriers to use. In a company environment, providing a smooth user experience and sufficient guidance for new AI tools should strengthen employees' intentions to use them. Therefore, we expect that effort expectancy will positively impact AI tool adoption at Nedap.

However, the influence of effort expectancy is also context-dependent (Khechine et al., 2016; Tamilmani et al., 2021; Venkatesh et al., 2003). Prior research indicates that ease of use may become less salient once employees gain experience with a technology, as familiarity reduces perceived effort over time (Venkatesh et al., 2003). For more advanced or expert users, overly simplified AI tools may even be perceived as restrictive, limiting flexibility or control rather than facilitating work (Brynjolfsson et al., 2025). In addition, when AI systems are embedded within complex workflows, perceived ease of use may be outweighed by concerns related to transparency, integration, or required changes to established work practices (Afroogh et al., 2024; Fetaji, 2023; Venkatesh, 2022). Nevertheless, when AI tools are perceived as intuitive and supportive of employees' workflows without constraining autonomy or flexibility, effort expectancy is likely to facilitate adoption. Therefore, I expect that effort expectancy will positively impact AI tool adoption at Nedap.

Social Influence (SI)

Social influence in UTAUT captures "the degree to which an individual perceives that important others believe he or she should use the system" (Venkatesh et al., 2003). This includes pressure or encouragement from colleagues, supervisors, or the broader work culture to use technology. If employees perceive that their peers and managers at Nedap believe that AI tools are valuable and expect them to use these tools, they are more likely to comply. Social influence has also been observed as a meaningful predictor of AI acceptance as well (Jain et al., 2022; Su et al., 2025). In collaborative workplaces, shared norms and leader support strongly shape the adoption of new tools. If managers present an AI analytics platform as an industry standard, employees often feel social and professional pressure to use it. In contrast, weak support or open doubt from coworkers can slow adoption.

On the other hand, the impact of social influence also depends on contextual and individual factors (Venkatesh et al., 2003). Prior research suggests that pressure may be less influential in settings where employees possess high levels of autonomy or domain expertise, as such individuals are more likely to trust their own judgment rather than follow what colleagues or managers expect (Venkatesh, 2022; Venkatesh et al., 2003). In addition, as AI becomes more commonly used in an organization, social influence may become less important. Over time, using AI can shift from a decision shaped by others to a regular habit. However, when endorsement from colleagues and supervisors aligns with employees' own assessments of usefulness and organizational support, social influence can still reinforce adoption (Jain et al., 2022). Thus, I expect social influence to increase employees' intentions to use AI, highlighting the roles of organizational culture and peer influence in technology acceptance.

Facilitating Conditions (FC)

Facilitating conditions refer to "the degree to which an individual believes that an organizational and technical infrastructure exists to support use of the system" (Venkatesh et al., 2003). This construct refers to having the right resources, knowledge, and support in place, such as access to hardware and software, training programs, and IT support. In a company like Nedap, these conditions could include a stable IT environment, help-desk support for AI and related technologies, and management providing time or incentives to learn the new tool. Venkatesh et al. (2003) originally posited that facilitating conditions directly influence actual usage, since even a willing user cannot proceed without support. However, especially in the early adoption stages, the perception of strong facilitating conditions can also strengthen a person's intention to use the system (Su et al., 2025). Empirical research on AI adoption has found that when employees feel that the organization has provided sufficient support and compatibility for the AI tools, they are more likely to intend to use them (Chatterjee et al., 2023; Su et al., 2025). If Nedap ensures that an AI tool fits smoothly into existing workflows and offers proper training, employees are more likely to feel confident and willing to use it.

On the other hand, the role of facilitating conditions may also vary depending on organizational and individual circumstances (Venkatesh, 2022; Venkatesh et al., 2003). Prior research indicates that once basic infrastructure and support are in place, facilitating conditions may become less salient for experienced users who are already capable of integrating AI tools into their workflows independently (Venkatesh et al., 2003) In contrast, for complex AI systems or during early adoption stages, insufficient training, unclear guidelines, or poor system compatibility can undermine employees' confidence and willingness to use the technology (Chowdhury et al., 2022; Su et al., 2025). Moreover, the mere availability of technical resources does not guarantee adoption if employees perceive a lack of managerial commitment or alignment with existing work practices (Afroogh et al., 2024). When facilitating conditions are perceived as comprehensive, reliable, and responsive to employees' needs, they can lower practical barriers and strengthen confidence in AI use (Chowdhury et al., 2022; Jain et al., 2022; Su et al., 2025). Therefore, I posit that facilitating conditions positively influence Nedap employees' intention to adopt and use AI and related technologies.

Hedonic Motivation (HM)

Hedonic Motivation is defined as "the fun or pleasure derived from using a technology" (Venkatesh et al., 2012). This construct represents the intrinsic enjoyment or satisfaction one derives from using a system, an emotional factor that UTAUT2 introduced to complement the more practical, utility-focused predictors. While workplace tools are often adopted for their utility, enjoyment can still play a role, particularly if the AI tool is engaging or novel. Venkatesh et al. (2012) found a strong positive relationship between the pleasure of using a technology and the intention to use it. The relevance of hedonic motivation in workplace AI adoption may depend on how employees interpret the role of enjoyment in professional contexts (Tamilmani et al., 2021). While curiosity and enjoyment can initially encourage people to try new AI tools, their impact may fade when using the technology is perceived as mandatory or judged mainly by how well it performs. In highly regulated or high-risk work settings, employees may place less value on enjoyment and focus more on reliability, accuracy, and responsibility (Dietvorst et al., 2015; Schmutz et al., 2024). Additionally, as AI use becomes routine, the excitement of trying something new is likely to fade, reducing the long-term motivational role of enjoyment (Venkatesh et al., 2012). When AI tools succeed in maintaining engagement without conflicting with professional norms or task demands, hedonic motivation can still contribute to employees' willingness to adopt and use them. Thus, I propose that hedonic motivation positively affects employees' willingness to use AI tools.

Habit (Ha)

Habit is "the extent to which people tend to perform behaviors automatically due to learning or prior experience" (Venkatesh et al., 2012). In other words, habits reflect how past usage of a technology (or similar systems) can form an automatic tendency to keep using it. If an employee has repeatedly used an AI tool to the point that it becomes a routine part of their workflow, that habit will strongly drive ongoing use and the adoption of new, similar technologies. UTAUT2 studies indicate that habit can directly influence both behavioral intention and actual technology use (Venkatesh et al., 2012). In a workplace scenario, if employees have already begun using AI tools in their daily lives, this habitual use will likely continue and grow into their work lives. Moreover, employees who are generally inclined to adopt new technology might automatically try out a provided AI tool with less resistance. At the same time, the influence of habit is not universally positive (Venkatesh et al., 2012). Established work routines may reinforce reliance on existing tools and processes, creating resistance to adopting new AI systems. In these situations, strong habits tied to traditional ways of working may slow down adoption (Dell'Acqua et al., 2025; Venkatesh et al., 2012). When prior experience with AI or similar technologies aligns with perceived usefulness and task requirements, habit is more likely to support sustained adoption (Tamilmani et al., 2021; Venkatesh et al., 2012). Therefore, I expect that employees' habits of technology use will positively influence their AI usage; those with established usage patterns or prior familiarity will likely adopt and continue using it.

Algorithmic Aversion (AA)

Algorithmic aversion refers to people's tendency to distrust or avoid algorithmic systems after observing them make mistakes, and prefer human judgment even when the algorithm is statistically superior (Dietvorst et al., 2015). In the workplace, algorithmic aversion can manifest as employees' reluctance to use an AI tool due to a lack of trust in the AI's decisions or outputs. For example, if an AI decision support system makes an error or an unexpected recommendation, employees might lose confidence in it faster than they would in a human colleague who makes a similar mistake, thereby reducing their willingness to adopt or use the technology. Empirical studies have consistently shown that low trust in AI is associated with reduced intention to use and underutilization of algorithmic recommendations (Afroogh et al., 2024; Dietvorst et al., 2015; Jain et al., 2022; Su et al., 2025).

At the same time, algorithmic aversion does not always negatively affect AI adoption. Research suggests that moderate skepticism toward AI can promote more deliberate use, particularly in high-stakes or complex contexts where blind reliance on automated systems may be risky (Afroogh et al., 2024). Exposure, experience, and opportunities for human oversight have been shown to reduce initial aversion, as users learn when and how AI systems perform well (Dietvorst et al., 2015; Johnson et al., 2023). In addition, providing explanations, feedback, and clear accountability structures can mitigate distrust and transform aversion into informed engagement rather than outright rejection (Afroogh et al., 2024; Chowdhury et al., 2022; Su et al., 2025). Nevertheless, when algorithmic aversion remains high and trust is low, employees are more likely to avoid or underuse AI tools, limiting their potential benefits. Therefore, we posit that algorithmic aversion negatively influences Nedap employees' intention to adopt and use AI and related technologies.

Organizational Trust (OT)

Organizational trust is the confidence employees have that the people and systems in their organization act reliably, fairly, and with integrity (Mayer et al., 1995). It encompasses trust in management decisions, trust in colleagues, and trust in the organization's technical systems. High organizational trust means employees are willing to be vulnerable to new initiatives, such as AI implementation, because they expect positive outcomes and support from their organization. In this context, organizational trust plays a pivotal role in reducing resistance to new technologies. Conversely, when trust in management is high, but communication about AI objectives, limitations, or accountability is unclear, employees may experience confusion or uncertainty rather than reassurance (Kelley, 2022). When organizational trust is accompanied by transparency, employee involvement, and clear governance structures, it is more likely to foster constructive engagement with AI technologies. I propose that when organizational trust is high, employees will exhibit greater acceptance and use of AI tools provided by the company.

Hypothesis and the Mixed-Method Approach

Building on the Unified Theory of Acceptance and Use of Technology (UTAUT) and its extensions, this study applies the framework to understand the key factors shaping employees' adoption and use of AI tools at Nedap. By examining both core UTAUT constructs and additional factors related to motivation, habit, and trust, the study seeks to explain variations in AI adoption behavior within the organizational context. While the framework specifies theoretically grounded relationships between these constructs and employees' intention to use AI, empirical investigation is required to assess whether and how these relationships manifest within the organizational context.

To this end, a quantitative survey is employed as the primary method to test the hypothesized relationships derived from the extended UTAUT framework. This approach enables a systematic examination of the direction and strength of the causal effects of the proposed determinants on employees' intention to use AI and related technologies. Based on the theoretical framework, the following hypothesis is proposed:

> ***Hypothesis****: Performance expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilating Conditions (FC), Hedonic Motivation (HM), Habit (Ha), Organizational Trust (OT) positively and Algorithmic Aversion (AA) negatively influence employees' intention to use AI and related technologies at the workplace.*

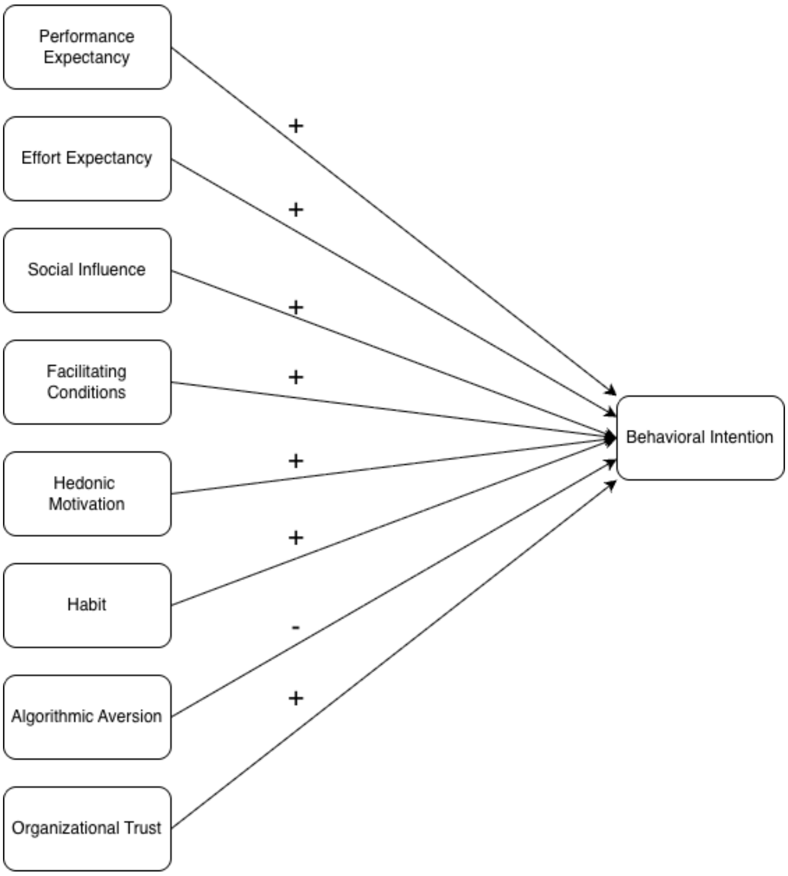

Figure 1

Proposed Theoretical Model

Although the quantitative approach is well-suited for hypothesis testing and identifying statistically significant relationships, it offers limited insight into the underlying reasons why certain constructs may exert stronger or weaker effects across different employee groups or usage contexts. Specifically, survey data alone cannot fully capture employees' subjective experiences, perceptions, and contextual considerations related to AI use. Therefore, qualitative interviews are conducted to complement the quantitative findings. The interviews provide deeper insight into how employees interpret and experience AI tools in their daily work, and they enable the exploration of contextual and situational factors that help explain patterns observed in the survey results. By integrating quantitative and qualitative methods, this mixed-method approach supports both rigorous theory testing and a richer understanding of the mechanisms and boundary conditions shaping workplace AI adoption at Nedap.

In addition to explanation, this study incorporates an intervention component to translate empirical insights into actionable organizational improvements. The intervention is informed by both the quantitative and qualitative findings and aims to address key barriers and facilitators of AI adoption identified within the Nedap context. By designing and reflecting on a targeted intervention, the study moves beyond descriptive and explanatory analysis to generate practical recommendations, thereby strengthening the research's relevance for organizational decision-making and responsible AI implementation.

Quantitative Strand: Survey

Method

Participants and Sampling

The target population for this study consisted of all employees at Nedap. The survey invitation was distributed to every employee via internal communication channels, including the company's email systems, news feed, and Slack workspace. Because every member of the organization was invited to participate, the sampling design followed an attempted census approach rather than a probabilistic sampling strategy. This design aimed to capture data from the entire employee population rather than from a subset.

Participation was entirely voluntary. Consequently, the final dataset reflects a self-selected sample of respondents drawn from the full employee population. While this approach offers the potential for comprehensive coverage, it is subject to non-response bias and self-selection bias, as employees who chose to respond may systematically differ from those who did not (Groves et al., 2009). To mitigate these risks, reminders were issued through multiple channels to encourage participation and enhance response rates, following best practices for survey engagement in an organizational context recommended by Dillman et al. (2014).

A total of 97 responses were collected, representing roughly 10% of Nedap's total employees. The summary of demographic characteristics is shown in Table 1. The age distribution skews mid-career: 25–34 years (43.3%) and 35–44 years (38.1%) together account for 81.4% of the sample, with smaller shares aged 18–24 (7.2%), 45–54 (10.3%), and 55+ (1.0%). Representation across business units is uneven, with nearly half of respondents from Healthcare (49.5%), followed by Retail (23.7%) and General (10.3%), while Livestock (9.3%), Security (4.1%), and IT (3.1%) are less represented. Overall, the sample is concentrated among mid-career employees and the Healthcare unit. This pattern could limit the extent to which the results can be treated as fully representative of Nedap as a whole; rather, they should be viewed as reflecting the perspectives of the subset of employees who completed the survey.

Table 1

Demographic profile of survey respondent

Demographics		N	%
Age			
	18-24	7	7.2%
	25-34	42	43.3%
	35-44	37	38.1%
	45-54	10	10.3%
	55+	1	1.0%
Business Unit			
	General	10	10.3%
	Healthcare	48	49.5%
	IT	3	3.1%
	Livestock	9	9.3%
	Retail	23	23.7%
	Security	4	4.1%

Measures

The survey instrument (available in Appendix A) was adapted from validated scales in prior UTAUT and UTAUT2 studies (Venkatesh et al., 2003, 2012), expanded with two additional predictors: Algorithmic Aversion and Organizational Trust, to better reflect AI-specific and workplace governance factors. All items were measured on a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree), except for Behavioral Intention items, which used a 0-to-10 scale to capture finer variation in willingness to adopt.

Performance Expectancy (PE), Effort Expectancy (EE), Social Influence (SI), Facilitating Conditions (FC), Hedonic Motivation (HM), and Habit (Ha) were adapted from classic UTAUT/UTAUT2 scales and rephrased to refer specifically to "AI tools" and organizational settings. Items on Algorithmic Aversion (AA) were influenced by validated items from studies by Su et al. (2025) and Jain et al. (2022). The last construct, Organizational Trust (OT), has rarely been incorporated into research about AI adoption, so its items were formulated based on the Model of Trust given by Mayer et al. (1995). These items were also reviewed by a few Nedap employees to ensure they fit with the company's context. Each item was presented in two versions, depending on respondents' AI usage frequency. For employees who reported using AI tools less than once per week, items were framed hypothetically (e.g., "I believe using AI tools could be useful in my job."), whereas for those using AI tools at least weekly, items were worded to reflect actual use (e.g., "I believe using AI tools is useful in my job.").

Data Analysis

Survey data were processed and analyzed using Python, R, and SmartPLS 4. Although the survey consisted of two versions, they were merged prior to analysis. This decision was made because the underlying constructs, item content, and response scales were identical across versions, differing only in verb tense to accommodate respondents' usage experience. Analyzing the versions separately was not feasible due to the very small number of respondents in the hypothetical-use condition (n = 4), which would not allow for reliable statistical comparisons or stable model estimation. Python was used first to clean and prepare the merged dataset, including removing metadata fields, filtering respondents, recoding categorical variables into numerical scales, and reverse-coding negatively phrased items. This pre-processing step ensured a consistent, analysis-ready dataset.

Following data preparation, R was used to describe the cleaned dataset and explore its underlying structure. First, R produced basic descriptive statistics to summarize the demographic profile of respondents and give an initial overview of the survey variables. Principal Component Analysis (PCA), supported by parallel analysis, was then conducted to identify groups of items that measured similar underlying concepts. This helped reduce the original survey items into meaningful factors and guided the creation of composite scales for Attitude, Subjective Norms, Perceived Behavioral Control, and Trust. In addition, R was used to calculate Spearman correlations between demographic variables, the composite constructs, and behavioral intention, providing an initial view of how the key variables in the study were related.

To examine how the main constructs relate to behavioral intention, Partial Least Squares Structural Equation Modeling (PLS-SEM) was carried out in SmartPLS 4 using bootstrapping (5,000 resamples). PLS-SEM was chosen because it is proven to work well with smaller samples and models that include several latent variables, making it suitable for this study's exploratory aims (Hair et al., 2021; Sarstedt et al., 2021). Unlike traditional SEM, PLS-SEM places fewer assumptions on the data and focuses on explaining as much variance as possible in key outcomes (Hair et al., 2019). Compared to simple linear regression, which analyzes one relationship at a time and relies on observed scale scores, PLS-SEM allows multiple relationships to be tested simultaneously and directly models the underlying constructs rather than just their averaged items. This approach also accounts for measurement error, resulting in more reliable estimates (Becker et al., 2012). Bootstrapping was used to evaluate the significance and stability of the model's paths, providing evidence of how Attitude, Subjective Norms, Perceived Behavioral Control, and Trust predict employees' intention to use AI tools.

Principal Component Analysis

After confirming that all collected responses were eligible, principal component analysis was performed on 37 survey items using the Varimax rotation method. Factor solutions are based on eigenvalues > 1 (the Kaiser-Guttman criterion), indicating whether a component explains more variance than a single original variable in the data set (Fabrigar et al., 1999). The returned results indicated that there are four sufficient constructs, as presented in Table 2. After removing nine items (indicated in Appendix A) that do not load on any of the constructs, Cronbach's alpha was calculated for each construct (Taber, 2018). All four constructs showed results greater than .7, indicating high reliability.

Although the survey instrument was originally grounded in the UTAUT and UTAUT2 frameworks, the factor-analytic results showed a structure that resonates more closely with the Theory of Planned Behavior (TPB) with Technology Trust as an additional predictor. As discussed above, UTAUT/UTAUT2 posit that technology adoption is shaped by performance beliefs, effort beliefs, social influence, and facilitating conditions; these constructs share conceptual roots with TPB's Attitude, Subjective Norms, and Perceived Behavioral Control (Ajzen, 1991; Venkatesh et al., 2003, 2012). The extracted factors, Attitude, Subjective Norms, Perceived Behavioral Control, and Trust, therefore, reflect a theoretical alignment. Perceptions of usefulness, enjoyment, and habitual use collectively form a broad Attitude construct; items related to management and peer expectations align with Subjective Norms; and perceptions of self-efficacy and ease of use correspond to Perceived Behavioral Control. Trust emerges as a distinct construct that extends TPB by capturing concerns specific to AI adoption, such as algorithmic reliability and the role of organizational oversight.

Table 2

Reliability and cross-loading (N = 97)

Construct	Loading	Mean	SD	α
Attitude (Eigenvalue = 12.17; Variance = 32.9%)		3.75	0.77	.94

Construct	Loading	Mean	SD	α
I believe using AI tools is useful in my job.	.70	4.41	0.67	
I believe using AI tools helps me accomplish tasks more quickly.	.68	4.09	0.89	
I believe using AI tools increases my productivity at work.	.71	4.07	0.88	
I believe using AI tools improves my overall job performance.	.70	4.89	0.97	
I believe AI tools enhance the quality of my work.	.68	3.65	1.13	
I believe using AI tools is fun.	.77	3,76	1.06	
I believe using AI tools is entertaining.	.69	3.56	1.15	
I enjoy using AI tools as part of my work.	.74	3.91	0.95	
I believe using AI tools makes my work more interesting.	.76	3.39	1.20	
I use AI tools outside of work.	.69	4.08	0.92	
Using AI tools at work has become a habit for me.	.71	3.92	1.04	
I would find it difficult to do my job without AI tools.	.68	2.31	1.10	
Subjective norms (Eigenvalue = 2.30; Variance = 6.2%)		3.80	0.67	.71
People who are important to me at work think I should use AI tools.	.68	3.38	1.09	
My colleagues encourage me to use AI tools.	.60	3.46	0.98	
Management in my company supports the use of AI tools.	.64	4.39	0.70	
If I have trouble using AI tools, I believe I can get help from others in the company.	.61	3.96	0.83	
Perceived Behavioral Control (Eigenvalue = 2.73; Variance = 7.4%)		3.8	0.69	.87
I believe learning to use AI tools is easy for me.	.76	3.94	0.85	
I believe interaction with AI tools is clear and understandable.	.74	3.73	0.86	
I believe AI tools are easy to use.	.72	3.74	0.83	
I believe I can easily become skillful at using AI tools.	.75	3.73	0.80	
I believe I have the knowledge necessary to use AI tools.	.74	3.88	0.93	
Trust (Eigenvalue = 3.54; Variance = 9.6%)		3.43	0.76	.87
I believe AI tools could provide accurate information.	.64	2.71	1.03	
I believe AI tools could provide reliable information.	.68	2.60	1.08	

Construct	Loading	Mean	SD	α
I trust that Nedap's AI use policies effectively protect sensitive data and my privacy.	.72	4.01	0.93	
I believe Nedap's guidelines ensure that AI tools are used in an ethical and responsible manner.	.62	3.79	0.91	
I have confidence that management provides proper oversight of AI algorithms to prevent unfair and biased outcomes.	.73	3.20	1.17	
I trust Nedap to handle and use AI training data in a way that respects privacy and security policies.	.78	3.98	0.96	
I am confident that the company will enforce its AI-related policies and address any misuse of AI tools promptly.	.70	3.72	0.97	
Behavioral Intention		8.75	1.68	

Results

Descriptive and Correlation Analysis

Descriptive statistics were first examined to provide an overview of respondents' evaluations of the main study constructs. Table 2 presents the means and standard deviations, while table 3 shows bivariate correlations among all variables. Overall, respondents reported moderately to highly positive evaluations across the core constructs. Attitude ($M = 3.75$, $SD = 0.77$), Subjective Norms ($M = 3.80$, $SD = 0.67$), Perceived Behavioral Control ($M = 3.80$, $SD = 0.69$), and Trust ($M = 3.43$, $SD = 0.76$) were all above the midpoint of their respective scales. Behavioral Intention (BI) to use AI tools was particularly high ($M = 8.75$, $SD = 1.68$), indicating a strong overall willingness among respondents to continue or increase their use of AI tools at work.

Correlation analysis showed that Behavioral Intention was positively and significantly associated with all four constructs. The strongest relationship was observed between Attitude and Behavioral Intention ($r = .62$, $p < .01$), followed by significant positive correlations with Trust ($r = .37$, $p < .01$), Subjective Norms ($r = .32$, $p < .01$), and Perceived Behavioral Control ($r = .32$, $p < .01$). These results suggest that more favorable evaluations of AI tools, higher trust, stronger perceived social support, and greater perceived control are all associated with higher intention to use AI tools.

In addition, Attitude was significantly correlated with the other core constructs. Attitude showed a moderate positive correlation with Trust ($r = .49$, $p < .01$), Subjective Norms ($r = .43$, $p < .01$), and Perceived Behavioral Control ($r = .41$, $p < .01$). These associations indicate that employees who hold more positive attitudes toward AI tools also tend to perceive greater trust, stronger social encouragement, and higher ease of use and self-efficacy.

Table 3

Correlations

Measures	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*
1. Age	1							
2. Gender	-.11	1						
3. Business Unit	-.04	-.18	1					
4. Attitude	-.08	-.03	-.02	1				
5. Subjective Norms	-.15	.03	-.24*	.43**	1			
6. Perceived Behavioral Control	-.11	-.17	.11	.41**	.16	1		
7. Trust	-.01	.12	-.12	.49**	.24*	.09	1	
8. Behavioral Intention	.02	-.19	.04	.62**	.32**	.32**	.37**	1

** Correlation is significant at the .01 level (2-tailed).

* Correlation is significant at the .05 level (2-tailed).

SEM Analysis

Bootstrapped PLS-SEM estimates were used to examine which of the four constructs, Attitude, Subjective Norms, Perceived Behavioral Control, and Trust, significantly predicted employees' Behavioral Intention (BI) to use AI tools. Table 4 summarizes the path coefficients and p-values. Descriptive statistics showed a high overall level of Behavioral Intention to use AI tools, with a mean score of 8.75 and a standard deviation of 1.68. This indicates that respondents generally reported a strong willingness to continue or increase their use of AI tools in their work.

Table 4

PLS-SEM results

Predictor variables	Behavioral Intention β
Attitude	.58 ***
Subjective Norms	.01
Perceived Behavioral Control	.03
Trust	.22*
Adjusted R^2	.53 ***

*p < .05; **p < .01; ***p < .001

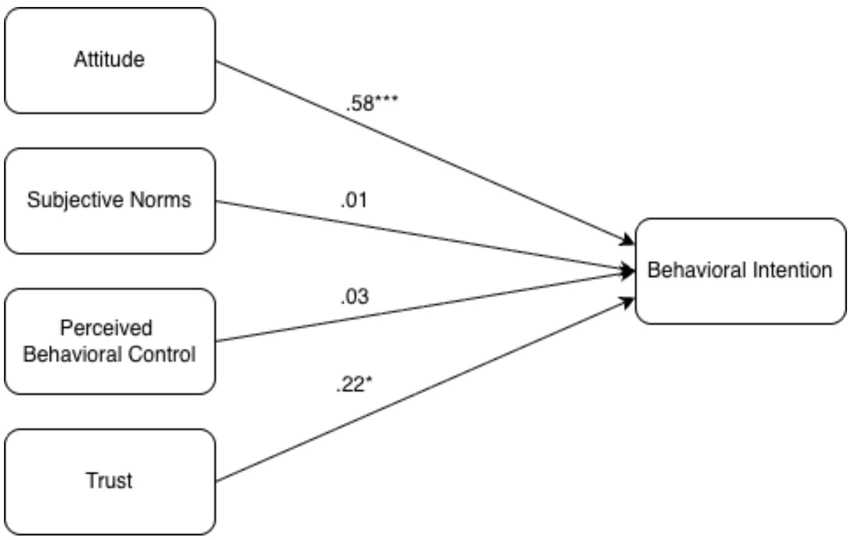

Figure 2

Result model

Attitude showed the strongest and most significant effect on BI ($\beta = .58$, $t(92) = 7.09$, $p < .001$), indicating that more positive attitudes toward AI tools are strongly associated with a higher intention to use them. Trust also had a significant positive effect on BI ($\beta = .22$, $t(92) = 2.30$, $p < .05$), suggesting that employees who have greater confidence in the organization's AI governance and the reliability of AI tools are more willing to adopt them. In contrast, Perceived Behavioral Control ($\beta = .03$, $t(92) = 0.36$, $p = .721$) and Subjective Norms ($\beta = .01$, $t(92) = 0.10$, $p = .919$) did not significantly predict BI in this model. This means that ease-of-use beliefs and social expectations did not show a statistically significant relationship with BI when included alongside attitude and trust.

The model's adjusted R^2 for Behavioral Intention was .53, indicating that Attitude, Subjective

Norms, Perceived Behavioral Control, and Trust together explained 53% of the variance in employees' intention to use AI tools. This level of explained variance is considered substantial in behavioral research.

Taken together, the hypothesis was not supported by the empirical model. Although the study initially hypothesized that UTAUT/UTAUT2 constructs, along with Trust in AI and Organization Trust, would positively influence employees' intention to use AI tools, the empirical findings do not support this model. Instead, the model converged into four factors consistent with a TPB structure, including Attitude, Subjective Norms, Perceived Behavioral Control, and Trust. Within this final model, only Attitude and Trust significantly predicted Behavioral Intention, while the remaining TPB constructs did not. As a result, the hypothesized UTAUT-based relationships are not confirmed in the final empirical model.

Qualitative Strand: Interview

Method

Purpose

The qualitative component complements the survey by providing deeper insight into employees' experiences and perceptions regarding AI use at Nedap. Specifically, it focuses on how employees integrate AI into their daily work and the outcomes they associate with its use. The interviews explore employees' practical experiences with AI, including challenges such as errors, misunderstandings, or workflow disruptions, as well as perceived impacts on learning, skill development, and job satisfaction.

Participants and Sampling

Participants for the interviews were recruited through a self-registration process embedded at the end of the survey. After completing the survey, respondents were prompted to indicate whether they were willing to participate in a follow-up interview. Those who expressed interest could voluntarily provide their contact details. At this stage, respondents were informed that providing contact information meant their survey responses were no longer anonymous.

From this pool of self-registered volunteers, interview participants were selected using purposive sampling. Selection was guided by the goal of capturing diverse and information-rich perspectives on AI use at Nedap, with particular attention to internal inconsistencies in survey responses, extreme scores, and nuanced or ambivalent evaluations of AI use. Survey data were reviewed to identify respondents whose answers deviated from dominant patterns or reflected tensions between perceived ease of use, trust, and perceived reliability. For example, a respondent reported low agreement with statements indicating that AI tools are easy to use, while agreeing that learning to use these tools is easy and interaction with them is clear and understandable. This approach allowed the qualitative data to deepen the understanding of the findings emerging from the quantitative data. Additionally, participants were deliberately chosen to represent a broad range of Behavioral Intention (BI) scores, ensuring coverage from low to high intention to use AI tools. This strategy enabled the exploration of differences in experiences, motivation, and perceived outcomes across varying levels of willingness to adopt AI.

In total, seven participants were selected and interviewed. This number was considered appropriate to capture a range of perspectives while keeping the dataset manageable for in-depth, qualitative analysis. The focus was on obtaining rich, detailed accounts from each participant rather than achieving numerical representativeness, consistent with the exploratory nature of semi-structured interviews (Wilson, 2014).

Data Collection

Semi-structured interviews were conducted to capture nuanced experiences while allowing participants to elaborate on their individual perspectives. All interviews were conducted by the researcher, who was an intern at Nedap during data collection but did not hold a managerial or evaluative role with respect to the participants. This position provided familiarity with the organization while also requiring careful reflection on how it might affect data collection and interpretation. Each interview lasted approximately 30 minutes and was held either in person or online via Microsoft Teams / Zoom. All sessions were audio-recorded with consent and transcribed verbatim. The interview guide consisted of five main sections:

1. **Introduction:** Purpose explanation, confidentiality assurance, and background questions about the participant's role and tenure.
2. **AI Use in Daily Work:** Exploration of how participants incorporate AI tools into workflows, including common tasks and perceived usefulness.
3. **Errors and Workflow Disruptions:** Identification of AI-related errors, misunderstandings, and coping strategies.
4. **Perceived Outcomes:** Reflection on AI's impact on personal development, skill-building, collaboration, creativity, and job satisfaction.
5. **Closing:** Open discussion of improvements and future expectations for AI use at Nedap.

The interview guide provided a general structure to ensure consistency across interviews; however, the interviews were not fully standardized. In addition to the core set of questions, each participant received several tailored follow-up questions based on their individual survey responses. These personalized questions were designed to prompt participants to clarify, explain, or elaborate on specific patterns, contradictions, or noteworthy points identified in the quantitative data. This adaptive approach enabled the interviews to build directly on the survey findings and to support a deeper understanding of participants' reasoning, experiences, and interpretations.

Data Analysis

Interview transcripts were analyzed using thematic analysis (Braun & Clarke, 2006). The analysis was assisted by ATLAS.ti, which was used to organize transcripts and apply codes. An initial coding scheme was developed prior to coding based on the study's research questions (RQ2a and RQ2b) and insights from the quantitative survey. This preliminary codebook included categories related to *AI use context*, *error types*, *perceived outcomes*, such as learning, creativity, and job satisfaction. This deductive structure ensured alignment between the qualitative analysis and the overall goal of the study.

Coding proceeded iteratively. First, all transcripts were read multiple times to achieve familiarity with the data. The initial codebook was then applied to the transcripts in ATLAS.ti. During this process, codes were refined, merged, or expanded when interview data revealed nuances or themes not fully captured by the initial scheme. This inductive refinement allowed new sub-themes to emerge while maintaining consistency with the overarching analytical framework. Constant comparison was used throughout the coding process to examine similarities and differences across participants, particularly in relation to contrasting levels of AI use and behavioral intention.

After coding was completed, codes were grouped into higher-level themes that represented recurring patterns across interviews. These themes were reviewed and refined to ensure internal coherence and clear distinctions between themes. The final thematic structure was then interpreted in relation to the research questions and integrated with the quantitative findings to provide a richer, contextualized understanding of employees' experiences with AI use at Nedap. The finalized coding scheme, along with illustrative examples from the interview data, is presented in Appendix C.

Result

The interview findings show that AI tools are part of employees' daily work and that their use is influenced by task characteristics, personal preferences, and work context. Participants described using AI in specific tasks, especially in uncertain situations, and explained how they see the limits between human judgment and automated support.

AI Use

Across interviews, employees described AI as a highly integrated but task-specific support tool in their daily work. Rather than replacing core job responsibilities, AI was mainly used to reduce friction, speed up routine tasks, and provide a starting point when expertise or clarity was lacking. This positioning of AI as an assistant rather than an autonomous decision-maker suggests that participants maintained clear boundaries between human judgment and AI-supported input.

Employees reported using AI for a wide range of activities, including technical problem-solving, writing and language support, summarization, ideation, and coding assistance. For example, a support specialist explained that ChatGPT was mainly used to clarify technical uncertainty:

> *It's mainly ChatGPT, and it's used for technical questions. With support, we answer questions about a database where all the information from the organizations are and sometimes it has different behavior than what the customer expects, and we also have to use SQL, so sometimes if I'm not entirely sure of how to find or use a query, I will ask ChatGPT. Same goes for APIs. It's possible to retrieve information via the API, and sometimes there is a complex technical error message that I don't fully understand. And then I ask ChatGPT to clarify it in simple terms [...].*
>
> - Interviewee 1

Here, AI functions as a translation layer between complex technical problems and the employee's existing expertise. The participant remains responsible for diagnosing the issue and responding to the customer, while AI reduces cognitive load by translating technical uncertainty into more accessible terms. This suggests that AI supports making sense of things rather than making decisions, reinforcing the assistant role rather than an autonomous one.

Similarly, participants whose role is also communication-focused mentioned language and writing support as a core use case. One participant described building a custom GPT to support Dutch writing:

> *I built a GPT for myself to help me improve my emails, my different release notes that I write, and combined that with our (Nedap) style guide, making sure that when I write certain elements or certain things, that it gives me feedback.*
>
> - Interviewee 2

This example demonstrates a purposeful adaptation of AI to organizational practices. Instead of relying on generic outputs, the participants embed organizational norms within the tool. The AI does not generate content independently, but instead provides feedback and suggestions that the employee can accept or reject. This further supports the interpretation of AI as a reflective aid that enhances refinement and consistency while maintaining human authorship and accountability.

In more technical roles, AI tools such as Copilot, Cursor, Claude, or IntelliJ AI were described as deeply embedded in coding workflows, but often limited to small, well-defined tasks:

So right now I mostly use the IntelliJ AI integration. I've also tried Cursor [...] and most things that came along. Every time a new version comes out I try again, but I mostly use it for rubbing-ducking purposes, working on solutions, seeing if there's alternatives I missed. I use it for small, concentrated bits of code where I know exactly what I want there, and I know it's not too complicated. Sometimes I tell it to make unit tests. Stuff like that, like limited in scope

- Interviewee 5

The emphasis on "limited in scope" and "rubbing-ducking purposes" indicates that AI is valued mainly for reasoning support and verification rather than for end-to-end problem solving. This suggests that employees actively manage risk by restricting AI involvement to areas where errors are easily identified and corrected. Such selective use reflects an underlying calibration of trust; AI is useful, but not relied upon for complex or high-impact decisions.

Across roles, AI was often framed as a time-saving and efficiency-enhancing tool, particularly valuable when users "did not know where to start". As one participant noted:

If you don't know where to start, it's better to have ten possibilities than none.

- Interviewee 1

This framing positions AI as a generator of options rather than as an answer-giver. The value does not lie in correctness, but in providing an initial starting point from which the employee can proceed. This interpretation is supported by another participant's reflection on onboarding and learning a new system:

When I joined the company, maybe two weeks in, there was an incident with a tool. And in the past, what I would have done is go read the manual. Probably spend at least two days, then try to experiment on my own. Maybe fail. With access to AI, I would be able to tell it: "Hey, I know these other systems. Can you explain this new one in the terms of those ones and maybe highlight the differences?" And that would be like 90% of the way there. At that point, I then have to just look at the difference to understand the manual.

- Interviewee 6

Here, AI is framed as a learning aid that accelerates learning by connecting new information to existing known information. Importantly, the participant still engaged with the manual and final details, indicating that AI lowers the initial barrier to understanding rather than replacing formal documentation or expertise.

Taken together, these accounts indicate that AI is used mainly as a first filter, a means of speeding up work, or a cognitive aid, rather than as a substitute for human judgment. The outcomes described by participants point not to radical transformation of work practices, but to incremental gains in autonomy, speed, and confidence, particularly in situations characterized by uncertainty or time pressure. This consistent positioning across roles indicates that employees actively shape AI use in ways that preserve human oversight and responsibility, reinforcing its role as an assistant embedded within, rather than in control of, everyday work practices.

Perceived Benefits of AI Use

AI tools were described as reducing time spent on routine or cognitively demanding tasks, allowing employees to focus on higher-value work. A recurring theme was that AI helped employees get started faster, often described as a tool to accelerate learning, particularly when they encountered unfamiliar tools, frameworks, or concepts during onboarding or task transitions. One participant described this function explicitly:

> *I use it extremely often as a learning tool. If you tell me right now, I'm using whatever framework to do this evaluation. I would type into ChatGPT. "What is this framework?" if I'm not familiar with it?*
>
> - Interviewee 6

This participant's example shows how AI functions as an on-demand explanatory resource, allowing employees to quickly develop a baseline understanding without disrupting their workflow. Instead of engaging in time-consuming searches or formal training, participants used AI to generate immediate instruction. This suggests that productivity gains come not only from automation, but from reduced time spent on learning and sense-making.

The ability to quickly generate direction was closely tied to perceived productivity gains. Several participants described AI as a time-saving tool that accelerated their workflow without fully automating tasks. A developer highlighted how even small gains accumulated over time:

> *It's a bit about speed. Sometimes you have like, a vague idea of what you want, and then you can just talk to the AI a bit and don't have to go find a colleague. [...] you can just talk to the AI and it will most usually you get something useful. So, it saves time and that's*

> *basically the main value [...]. It saves me time. It's little bits here and there, but it does add up.*
>
> - Interviewee 5

This account indicates that AI use lowers minor frictions in everyday work, such as waiting for colleagues or switching contexts to search for information. The participant does not frame AI as offering complete solutions, but as providing "something useful" that allows work to progress. Productivity gains, therefore, emerge from continuity of work rather than from huge increases in efficiency.

In more technical contexts, AI-assisted coding was also framed as a way of speeding up execution while maintaining human oversight. A data analyst described how Copilot automated repetitive coding tasks and supported review processes:

> *When I'm coding, it (Copilot) gives a lot of suggestions and automatically refactors a lot of code when I change something. So that's really nice. It really speeds up my work quite a lot. And right now we're also trying to use the Copilot for doing the reviews on our pull request. And that's also spot some things that maybe some of us have missed. So that's also a nice addition, although it doesn't work perfectly all the time.*
>
> - Interviewee 7

Here, AI is positioned as an execution and verification aid, rather than a replacement for expertise. The explicit comment that the tool "doesn't work perfectly all the time" underscores the necessity of human review. Productivity gains thus coexist with ongoing critical judgment, reinforcing the idea that efficiency improvements are achieved without giving up control.

Next to time saving, AI was also perceived as enabling employees to work at a higher level of abstraction. By offloading repetitive or mechanical tasks, users could concentrate on more complex or meaningful aspects of their roles. One participant described this shift explicitly:

> *You have to think about your work in a kind of a different way. It solves all the easy task. So, then the most of the work is doing the more difficult challenges. So, I can also imagine that the work is getting a bit harder or more challenging because I have to solve all the harder tasks.*
>
> - Interviewee 7

This reflection suggests that AI use may not simply make work easier, but rather reconfigures task composition. While repetitive tasks are reduced, employees are left with more complex tasks, potentially increasing cognitive demands. This indicates that productivity gains are accompanied by changes in skill requirements and perceived task difficulty.

In non-technical roles, productivity benefits were similarly evident. AI-supported text processing, summarization, and transcription reduced manual effort and saved substantial time. For instance, a decision coach described using AI to convert visual workshop materials into text:

> *We had big posters on which we wrote new goals or new strategy directions. I make pictures of them and I upload them in ChatGPT. And I asked GPT to type it out. [...] I have to change some. But if it's written quite well, ChatGPT does a really good job, and it saves me a lot, a couple of hours for the day.*
>
> - Interviewee 3

This example illustrates how AI reduces workloads, allowing employees to avoid intensive transcription work. The participant's recognition that corrections are again required underscores that AI output is regarded as provisional, reinforcing the role of AI as an assistant across different positions.

Productivity gains were also linked to reduced reliance on colleagues. Several participants noted that AI allowed them to resolve questions independently, increasing autonomy and efficiency. One participant explained:

> *I think that the main change is that I'm much more sufficient as an individual. I don't need to reach out as much to others to get help with stuff.* - Interviewee 6

This increased self-sufficiency suggests that AI functions as a first-line support system, changing patterns of collaboration without eliminating them. Rather than replacing interpersonal interaction, AI appears to handle simple queries, potentially reshaping how and when employees seek human assistance.

Beyond efficiency, participants highlighted several ways in which AI supported learning, confidence, and professional development, particularly for tasks outside their core expertise. AI was often described as a low-threshold learning partner that reduced dependence on colleagues and lowered the barrier to experimentation. Several participants emphasized how AI enabled them to learn new skills or operate in unfamiliar domains. For example, one support specialist described building a personal application with Cursor despite limited programming experience:

> *I made a website for myself that I run locally. [...] and with Cursor, I could make it because otherwise, I don't really have a lot of programming expertise, so I wouldn't know where to start.*
>
> - Interviewee 1

This account indicates that AI lowers entry barriers to new skill domains, enabling employees to engage in tasks that would previously have been inaccessible. Learning here is not formal or structured, but exploratory and practice-based, facilitated by AI's ability to provide immediate feedback and overall structure. Similarly, participants in communication-focused roles highlighted gains in confidence, particularly regarding language use:

> *It's given me a different level of confidence with my language because especially Dutch [...] that I know that I'm able to also write well in Dutch.*
>
> - Interviewee 2

This suggests that AI contributes not only to task performance but also to self-efficacy, reinforcing employees' willingness to engage in challenging tasks. Increased confidence, in turn, may further enhance autonomy and job satisfaction.

In terms of job satisfaction, participants often linked AI use to reduced frustration and a greater sense of autonomy. One interviewee explained:

> *It gets some frustration out of the way [...] when you don't know where to go, you at least have a first step to take.* - Interviewee 1

Here, AI's value lies less in providing solutions and more in helping people get started. By suggesting an initial direction, AI helps reduce feelings of being stuck, which participants associated with frustration and inefficiency.

Overall, employees saw AI as useful mainly because it gave them more independence, made tasks easier to carry out, and supported learning and confidence. Instead of replacing teamwork or expertise, AI was seen as a first source of help that allowed employees to get started, try unfamiliar tasks, and work more independently. These benefits were linked to feeling more capable and less frustrated. However, these benefits were not universally framed as increased enjoyment. Some participants noted trade-offs, such as reduced creativity or less satisfaction from reviewing AI-generated work rather than producing it themselves. Nevertheless, AI was broadly perceived as supportive of personal growth, particularly when used intentionally and critically.

Challenges and Limitations of AI Use

Despite widespread use, participants consistently reported encountering errors, misunderstandings, and limitations in AI outputs. These issues were rarely framed as technical malfunctions of the tools themselves. Instead, participants often attributed problems to human-AI interaction dynamics, such as unclear prompts, insufficient context, or the probabilistic nature of AI systems. A recurring theme was that AI produced plausible but incorrect or irrelevant outputs, especially when instructions were vague. One participant reflected on early struggles with Cursor and ChatGPT:

> *I did get a lot of errors when I used Cursor, and it was mainly because I wasn't specific enough. [...] I didn't fully understand myself what I want. [...] I think also when using ChatGPT, the most errors are getting results that are not ideal, was mainly because I wasn't myself clear enough about what I want.*
>
> \- Interviewee 1

This one highlights that AI errors often reflect user uncertainty. When participants themselves lacked clarity, AI outputs tended to amplify this ambiguity rather than resolve it. The perceived error is therefore not only a failure of the system, but also an indicator of incomplete problem formulation on the part of the user. This suggests that effective AI use requires a level of self-awareness and conceptual precision that may not always be present, particularly in exploratory or early-stage tasks.

Others described how AI would "fill in the gaps" on its own, leading to hallucinations or unwanted assumptions:

> *Sometimes it then creates completely something that I don't want because it fills in the gaps itself. And so, it hallucinates. You really have to double check and make sure that it is correct.* - Interviewee 2

This quotation highlights a central tension in AI-supported work. The same generative abilities that make AI valuable for ideation and efficiency also create a risk of assumptions. Participants did not view hallucinations as random errors, but as an expected outcome of AI systems attempting to fill gaps in missing information. Consequently, users stressed the need for ongoing verification, underscoring that AI outputs are regarded as provisional suggestions rather than definitive answers.

In technical contexts, errors were seen as manageable but persistent. Developers noted that AI often failed when tasks became too complex or context-heavy:

> *The tool just stops listening at certain points. [...] Once context becomes big it becomes really unreliable [...] it quickly loses the plot.*
>
> - Interviewee 5

This observation suggests that AI tools are perceived as effective for narrow, well-scoped tasks, yet unreliable when required to maintain coherence across extended or complex contexts. Consequently, participants adapted their usage strategies by limiting AI involvement to discrete subtasks, implicitly acknowledging and compensating for these constraints.

These issues occasionally disrupted workflows by requiring restarts, re-prompting, or manual correction, rather than causing complete breakdowns. One participant described how incorrect outputs could trap users in unproductive loops:

> *You kind of get in a rabbit hole [...] stuff you don't need and stuff that's just not true. If it's already in there, I feel you can't really get it out. So you better just throw it out and start again*
>
> - Interviewee 1

This account highlights how AI-generated errors, once introduced into an interaction, are difficult to eliminate. Assumptions made by the tools may persist across subsequent prompts, leading users to abandon the session altogether. The decision to "throw it out and start again" reflects the user's strategy for managing AI limitations, favoring reset over incremental correction.

Notably, most participants emphasized that such disruptions were annoying rather than obstructive, provided users remained critical and careful. Several explicitly described AI as something that should never be trusted blindly:

> *There's rarely a case when I expect the AI to be correct. I don't trust it at all [...] I just understand this is auto-complete on steroids.*
>
> - Interviewee 6

This statement reflects a calibration of trust, where AI is viewed as a probabilistic system for completing patterns rather than a dependable source of truth. By lowering expectations and reframing AI as an advanced form of auto-completion, participants mitigate the impact of errors and preserve their own sense of control and responsibility.

Overall, the challenges associated with AI use were primarily related to unreliable outputs, hallucinations, and the difficulty of formulating clear, precise prompts. Participants saw these problems less as technical faults and more as natural limits of systems based on probabilities, which require careful human input and verification. As a result, effective AI use depended on users' ability to remain critical, manage expectations, and actively correct or reset interactions, reinforcing the view that AI is a support tool rather than an independent one.

Together, the interview findings show that employees primarily use AI as a supportive, efficiency-oriented tool embedded in daily workflows. While errors and misunderstandings are common, they are generally manageable and anticipated. At the same time, AI enables learning, confidence building, and skill development, especially in areas where employees lack prior expertise. These results highlight AI's role as an augmentative technology, one that amplifies human capability while still requiring active human judgment and control.

Intervention

The interviews revealed that while employees at Nedap broadly perceived AI as useful and supportive, their experiences were frequently shaped by issues related to unreliable outputs, hallucinations, and difficulties in formulating clear and effective prompts. These challenges were not described as a big failure, but rather as recurring frictions that required additional effort, critical checking, and rework. In particular, participants emphasized that unclear and incomplete prompts often resulted in irrelevant or misleading outputs, which in turn undermined trust and efficiency. With this background, the intervention focused on improving the quality of human-AI interaction at the point where many of these issues originate: prompt formulation.

Rationale for the Intervention

The interview results showed that many AI-related problems were not caused solely by technical limitations, but by the interaction between users and these systems. Participants reported that AI "filled in the gaps" when prompts lacked sufficient context, leading to hallucination or unwanted assumptions. Several interviewees acknowledged that errors often reflected their own uncertainty or lack of clarity rather than purely system errors. This finding supports previous research showing that AI errors emerge through interaction, coming from the probabilistic nature of generative systems and from unclear or incomplete human input (Afroogh et al., 2024; Jain et al., 2022).

At the same time, participants demonstrated an awareness that better prompts tended to lead to better results. More experienced users described limiting task scope, breaking down complex problems, or iteratively refining instructions as coping strategies. However, these practices were mostly informal, unevenly distributed across users, and based on trial and error rather than structured guidance. This gap pointed to an opportunity for an intervention that could make effective prompting practices more visible and supported, reducing cognitive load, lowering entry barriers, and improving output reliability without requiring deep technical expertise.

In addition to the interview results, the survey findings also pointed to the need for an intervention focused on how employees interact with AI. The quantitative analysis showed that employees' intention to use AI was mainly shaped by their overall attitude toward AI and their trust in both the technology and the organization's rules around it. Perceived ease of use and social influence did not play a significant role. This suggests that AI adoption at Nedap is not limited by access or usability, but by whether interactions with AI are seen as reliable, meaningful, and helpful. Problems such as unclear prompts and unreliable outputs, therefore, threaten not only task performance but also employees' attitudes and trust in AI. This reinforces the importance of an intervention that improves the quality of human–AI interaction, rather than simply encouraging more AI use.

Taken together, the interview and survey findings indicate that the key challenges in workplace AI use lie not in the availability or basic usability of AI tools, but in the quality of interaction between users and these systems. The intervention, therefore, targeted two closely related issues: unreliable or hallucinatory AI outputs and the use of unclear, vague, or incomplete prompts. Rather than attempting to improve the underlying AI technology itself, the intervention focused on improving the conditions under which AI is used. By helping users express their intentions more clearly and fully, the intervention aimed to reduce confusion in AI interactions, improve perceived reliability, and encourage more thoughtful and trustworthy use of AI.

Concept of the Intervention

To address these challenges, a prototype application, *Prompt Coach*, was developed. The core idea of the application is to transform users' simple, vague, or unclear prompts into structured prompts that provide sufficient context and constraints for LLMs to perform tasks more effectively. Instead of expecting users to already know how to prompt "correctly", the tool acts as an intermediary, guiding them through the process of specifying their task. Conceptually, the *Prompt Coach* can be understood as a meta-layer on top of existing AI tools. It does not replace the underlying language model, nor does it aim to automate tasks independently. Rather, it supports users in articulating their goals, assumptions, and constraints before the task is handed off to an AI system. In doing so, the tool reflects the way many interviewees already approach AI use, which is as an assistant that depends on clear instructions and careful framing, rather than as an autonomous problem solver.

The Prompt Coach was designed to raise awareness of how prompting influences AI behavior while simultaneously improving immediate task outcomes. This dual goal aligns with the interview findings that AI can function as both a productivity aid and a learning tool. By making the structure of an effective prompt visible and actionable, the intervention also has the potential to contribute to longer-term skill development and more calibrated trust in AI outputs.

Functional Design

From a user perspective, the interaction with the Prompt Coach follows a structured but lightweight flow. First, users enter their initial prompt, which is typically short, informal, and under-specified, resembling how they would normally interact with tools like ChatGPT. This initial input serves as the starting point for the transformation process. Next, the system classifies the user's task into one of several predefined task categories. These categories were selected to reflect the most common AI use cases reported in the interviews, including summarizing documents, writing text, brainstorming ideas, programming, and explaining concepts. This classification step ensures that the subsequent guidance is tailored to the nature of the task rather than applying a generic approach.

Once the task type has been identified, the system retrieves a corresponding prompt template associated with that category. Each template represents a structured outline of the information typically required for that type of task, such as audience, tone, constraints, input data, or desired output format. Here, the templates do not prescribe specific content; instead, they highlight key dimensions where clarity is often required.

When the user's message is identified as an initial prompt, the Prompt Coach compares the user's input against the selected template. The app reviews the template as a checklist and determines which elements are missing or insufficiently specified. Based on this assessment, the system generates a set of clarifying questions to fill in the gaps. These questions are presented to the user in natural language and focus on factors likely to influence output quality. After the user responds to these clarifying questions, the system generates a structured prompt by integrating the original input, the selected template, and the user's answers. The resulting prompt is expected to be more explicit, constrained, and aligned with the task requirements, thereby reducing ambiguity for the language model.

A key design decision was to separate the clarification phase from the generation phase. This mirrors the iterative prompting strategies described by experienced interview participants, but externalizes them into a guided process that can also support less experienced users. By asking targeted questions, the Prompt Coach encourages users to reflect on their own intent and assumptions, rather than passively accepting AI-generated outputs.

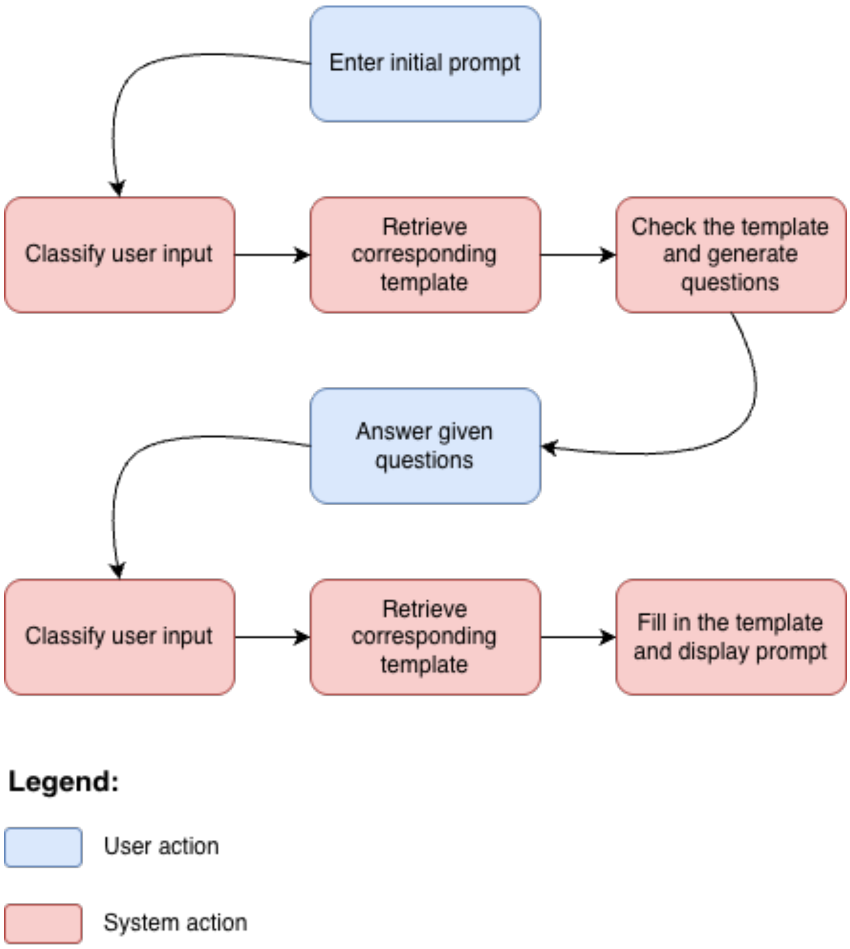

Figure 3

Basic functional design of Prompt Coach

Technical Implementation

On the technical side, the Prompt Coach was built using OpenAI's Agent Builder, a visual platform that supports the design of AI workflow without requiring extensive programming ("Agent Builder | OpenAI API," n.d.). Instead of writing complex code, the system was created by connecting different functional components into a structured workflow. This approach made it easier to experiment with and refine the application during development. The prototype's user interface was developed based on an existing OpenAI starter template (OpenAI, 2025). By relying on the OpenAI platform, the intervention could be developed rapidly and iteratively, in line with its exploratory and design-focused goals.

Figure 4

The app logic in Agent Builder

The workflow (shown in figure 4) begins with a Guardrails node, through which every user message is processed before entering the system's core logic. This node performs a set of automated checks to ensure safe and reliable operation, including moderation, detection of personally identifiable information, jailbreak and prompt injection detection, URL filtering, and hallucination risk assessment (node 1). Only messages that pass these checks are forwarded to the subsequent stages of the workflow. After this initial validation, the system determines whether the user message represents an initial prompt that needs to be transformed or a response to previously generated clarifying questions (node 2). This distinction is essential to route the interaction through the appropriate branch of the workflow. In both cases, an AI agent (nodes 3a and 3b) is then responsible for classifying the task type into one of the predefined categories (summarizing, writing, brainstorming, programming, or explaining concepts).

After classification, the system searches for the corresponding prompt template (nodes 4a and 4b). To simplify this process, templates were stored using a consistent naming convention based on task type. Once the template is retrieved, the subsequent logic depends on the interaction stage. For initial prompts, an agent (node 5a) evaluates which parts of the template are missing and generates clarifying questions accordingly. For follow-up messages containing user answers, another agent (node 5b) synthesizes the structured prompt by combining all available information.

This modular, agent-based architecture reflects the conceptual model of the Prompt Coach as a sequence of cognitive support steps rather than a single, unified system. Each agent has a clearly defined role, such as classification, gap detection, question generation, or prompt synthesis. This structure also makes the workflow extensible, allowing for future additions such as new task categories or alternative prompting strategies.

Positioning the Intervention

The Prompt Coach intervention directly addresses several themes that emerged from the interview data. First, it responds to concerns about unreliable outputs and hallucinations by reducing ambiguity at the input stage. While it cannot eliminate hallucinations entirely, it aims to reduce their likelihood by providing the AI with clearer instructions and constraints. This aligns with participants' strategies of limiting scope and being explicit, but lowers the effort required to do so.

Second, the intervention supports users with varying levels of AI experience. Less experienced users, who may not yet have developed effective prompting practices, receive structured guidance to help them articulate their needs. More experienced users can use the tool as a checklist or validation mechanism, ensuring that they have not overlooked important aspects of a task.

Third, the Prompt Coach supports calibrated trust rather than blind reliance. By making the prompting process explicit and interactive, it reinforces the idea that AI outputs depend heavily on human input. This may help users maintain a critical stance toward AI suggestions, consistent with the interview finding that employees rarely expect AI to be fully correct and instead treat it as "auto-complete on steroids."

Evaluation and Feedback

As an initial evaluation of the intervention, the Prompt Coach was demoed to a team within Nedap to gather qualitative feedback. The demo was conducted during a regular weekly team meeting. The session began with a brief explanation of the intervention's idea and purpose, followed by a walkthrough of how a user would interact with the tool. This evaluation was not intended as a formal effectiveness study, but rather as an exploratory assessment of perceived usefulness, usability, and potential improvements.

Overall, the feedback was positive. Team members agreed that the idea of a tool designed to transform vague prompts into structured ones was valuable and worth exploring further. They recognized that prompting is a critical yet often underestimated skill in AI use, and that a dedicated tool could raise awareness and improve outcomes.

At the same time, several constructive suggestions were raised. One concern was that the number of clarifying questions generated by the tool could become too long or too complex, potentially increasing cognitive load rather than reducing it. This feedback highlights a key design dilemma that while more detailed prompts can improve output quality, excessive questioning may discourage use, especially in time-pressured work contexts.

Another suggestion was to incorporate user background information as a form of memory within the application. By retaining contextual information about a user's role, domain knowledge, or typical tasks, the Prompt Coach could tailor its questions more effectively and avoid asking for information that is already implicitly known. This aligns with participants' descriptions of AI being most useful when it adapts to their existing expertise and context.

Finally, a more ambitious suggestion was about the overall interaction model. Instead of showing the structured prompt and requiring users to copy and paste it into another AI tool, team members proposed that the Prompt Coach could directly pass the generated prompt to another agent that performs the task. In this model, displaying the structured prompt would be optional, available only if users explicitly request it. Such an approach could further streamline workflows while preserving transparency and user control.

Discussion & Conclusion

Discussion of the findings

The goal of this study was to move beyond measuring AI adoption at Nedap and instead understand why employees use AI, how they use it in practice, and how value from AI use can be improved through targeted support. To achieve this goal, a mixed-method design was used: a quantitative survey grounded in UTAUT2 was used to examine determinants of Ai adoption, qualitative interviews explored lived experiences and outcomes of AI use, and a design-based intervention translated these insights into a support mechanism. Together, these components enabled both theoretical testing and practical exploration of AI use in a real organizational context.

The survey results show that employees' intention to use AI tools at Nedap is primarily driven by Attitude toward AI and Trust, rather than by Perceived Behavioral Control or Social Influence. Although the study initially adopted UTAUT and UTAUT2 as its guiding frameworks, the empirical evidence indicated that these constructs did not remain distinct. Instead, factor analysis revealed a structure more closely aligned with the TPB, consisting of Attitude, Subjective Norms, Perceived Behavioral Control, and Trust as an additional AI-specific predictor. While UTAUT offers a comprehensive framework by integrating multiple acceptance models, it may be less suitable for contexts where AI use is voluntary, exploratory, and embedded in knowledge work (Fetaji, 2023; Tamilmani et al., 2021). Compared to UTAUT/UTAUT2, TPB avoids dividing closely related constructs into multiple components, which in this study merged empirically (Ajzen, 2020; Rejali et al., 2023; Tamilmani et al., 2021). The convergence of UTAUT constructs into broader TPB dimensions suggests that, in this context, employees do not distinguish sharply between usefulness, enjoyment, and habit, but experience them as an integrated evaluative stance toward AI.

Attitude emerged as the strongest predictor of Behavioral Intention, suggesting that employees' overall evaluation of AI, combining perceived usefulness, enjoyment, and habitual use, dominates adoption decisions. Trust also showed a significant positive effect, highlighting that confidence in AI reliability and organizational governance is essential for willingness to use AI tools. In contrast, Subjective Norms and Perceived Behavioral Control did not significantly predict intention once Attitude and Trust were accounted for. These findings have important implications for AI adoption theory. The dominance of Attitude and Trust, combined with the non-significance of Perceived Behavioral Control and Subjective Norms, suggests that established adoption models may place too much emphasis on control and compliance in contexts where AI use is voluntary, professional, and already normalized. In these settings, employees' decisions to use AI are shaped less by external pressure, formal expectations, or ease of use, and more by whether AI is seen as meaningful, valuable, and trustworthy in everyday practice.

The interviews provide crucial context to these quantitative findings by showing how AI is embedded in everyday work. Employees consistently described AI as an assistive and augmentative tool, rather than a decision-maker or autonomous agent. Across roles, AI was used to reduce friction, improve learning, and generate starting points in situations of uncertainty. This explains why Attitude plays such a central role: AI is valued not simply because it is easy or expected, but because it meaningfully supports sense-making, learning, and autonomy. The interviews also shed light on why Trust matters. Participants frequently encountered hallucinations, irrelevant outputs, or context loss, but these issues were generally anticipated and managed through verification, task scoping, and critical judgment. Trust, therefore, was not blind reliance on AI accuracy, but calibrated trust—confidence that AI can be useful when handled carefully and that the organization provides sufficient governance and safeguards. This understanding of trust helps explain why it emerges as a significant predictor in the survey model. In terms of outcomes, employees associated AI use with productivity gains, reduced frustration, increased self-sufficiency, and opportunities for learning and skill development, particularly in unfamiliar domains. However, these benefits were incremental rather than transformative, reinforcing the idea that AI reshapes work practices subtly by lowering barriers and redistributing cognitive effort, rather than radically replacing tasks or roles (Dell'Acqua et al., 2023, 2025; Schmutz et al., 2024).

The intervention directly responded to the interview findings by targeting one of the most persistent sources of friction: unclear prompting. The Prompt Coach prototype translated existing coping strategies, such as task scoping and iterative clarification, into a structured process. Feedback from the demonstration suggests that employees viewed prompting as an essential yet under-supported skill and believe the intervention could improve output quality and reduce frustration. Importantly, the intervention reinforced the previous findings that effective AI use depends less on technical expertise and more on the quality of interaction (Afroogh et al., 2024; Johnson et al., 2023). By making the prompting process explicit, the Prompt Coach also supports learning and calibrated trust, aligning with the study's empirical emphasis on Attitude and Trust as key drivers of adoption.

Theoretical and Practical Implications

From a theoretical perspective, this study supports a shift toward more parsimonious models of AI adoption in organizational contexts where use is voluntary and exploratory. Predictors that are treated as separate in UTAUT and UTAUT2 empirically converged into broader constructs aligned with the Theory of Planned Behavior. This indicates that they are not always cognitively or experientially separable in everyday AI use. At the same time, the study highlights Trust as a distinct and necessary extension to TPB in AI contexts. Unlike many traditional information systems, generative AI systems are probabilistic, opaque, and prone to error, introducing uncertainty that existing adoption models do not fully capture. Incorporating trust, therefore, allows them to better reflect how users evaluate not only instrumental value, but also reliability, risk, and organizational safeguards. Rather than replacing established models such as TPB or UTAUT, this study suggests that AI adoption may be most effectively understood through a framework augmented with trust-related constructs, particularly in organizational settings characterized by low access barriers and active experimentation.

Practically, the study offers actionable insights for organizations adopting AI. First, fostering positive attitudes toward AI through meaningful use cases and autonomy may be more effective than relying on social pressure or mandates. Second, organizational trust and clear AI governance play a crucial role in sustaining adoption. Third, organizations should invest not only in AI tools themselves, but also in support mechanisms that improve human-AI interaction, such as prompting guidance, shared best practices, and reflective use. Interventions like the Prompt Coach illustrate how relatively lightweight design solutions can address common barriers and help translate AI adoption into tangible value.

Limitations of the study

The survey component is limited by its sampling characteristics. Although the survey followed an attempted census approach, participation was voluntary and resulted in a relatively small sample (N = 97), representing roughly 10% of the total employees. While an attempted census was used, participation bias likely influenced the results. After the survey had been distributed via Nedap's general channel on Slack, the researcher became aware that Slack channels are not used equally across business units. For example, Livestock or Security unit relies primarily on Microsoft Teams, which lacks unit-wide communication channels. As a result, some units were underrepresented. To mitigate this, the researchers reached out to contacts within these units and asked them to forward the survey. However, this additional effort proved only partially effective, and participation from these units remained limited. These imbalances in distribution may have favored positive attitudes toward AI and reduced variance in Attitude perceptions, potentially explaining the non-significance of Subjective Norms and Perceived Behavioral Control.

As a qualitative method, interviews are inherently subjective and rely on self-reported behavior. Participants may overestimate benefits, underestimate errors, or rationalize their AI use retrospectively (Demirci, 2024). Moreover, the small number of participants and the purposive sampling strategy prioritize depth over representativeness. While this aligns with the exploratory aim, it limits the ability to generalize findings across the organization (Ahmad & Wilkins, 2024; Gamble & Hewlett, 2025). Interviews capture perceptions rather than actual AI usage behavior; future studies could strengthen validity by incorporating observational or log-based data.

Third, the Prompt Coach intervention was constrained by the technical limitations of the chosen prototyping platform. While suitable for rapid development, the Agent Builder lacks external integrations, limiting personalization, contextual grounding, and adaptability to complex tasks. The intervention was evaluated only qualitatively and in a demo setting, meaning no objective performance or adoption effects could be measured. As a result, conclusions about effectiveness remain exploratory.

Another limitation of this study concerns the specific organizational context in which it was conducted. Nedap is an organization with relatively high digital maturity, strong professional autonomy, and a permissive attitude toward experimenting with AI. AI use was voluntary, access barriers were low, and employees were encouraged to explore AI tools in their own work. These conditions likely strengthened the role of experiential and evaluative factors, such as Attitude and Trust, while weakening the influence of Perceived Behavioral Control and Subjective Norms. In organizations where AI use is mandatory, tightly regulated, or closely linked to performance monitoring, adoption dynamics may look very different. In such settings, social pressure, formal rules, and perceived limits on control may play a much larger role in shaping AI use. Likewise, in organizations with lower AI familiarity, restricted access, or higher perceived risks, trust in AI may develop differently (Wu & Lederer, 2009). Therefore, the findings of this study are best seen as applying to organizations where AI use is voluntary and experimentation is encouraged, rather than as broadly representative of all workplace AI adoption contexts.

Conclusion

This study examined workplace AI use at Nedap through a mixed-method approach to understand adoption drivers, usage practices, and opportunities for design intervention. The findings show that employees' intention to use AI is primarily shaped by positive attitudes and trust in both AI systems and organizational governance, rather than by behavioral control or social influence. Employees use AI mainly as an assistive tool that supports learning, efficiency, and autonomy, while actively managing its limitations through critical judgment. The design-based intervention demonstrates that improving human–AI interaction, particularly at the prompting level, offers a promising pathway for enhancing AI value. Together, these results suggest that organizations should focus less on encouraging adoption itself and more on fostering meaningful, trustworthy, and well-supported AI use.

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Appendix A

Survey Instrument: AI and Related Technologies Adoption at Nedap

Demographic Information

1. How old are you?
2. What is your gender?
3. Which business unit do you work for?
4. Do you regularly use AI tools in your work (at least once a week)?

Behavioral Intention

5. *(Ver. A)* In the future, I intend to continue using (new) AI tools in my work.

5. *(Ver. B)* In the future, I intend to use AI tools more often in my work.

Usage Behavior

7. *(Ver. A)* I use AI tools for:
    - Programming / Coding
    - Writing
    - Automation
    - Research
    - Data analysis
    - Brainstorming / Ideation
    - Communication support
    - Learning / Skill Development
    - Design and visualization
    - Decision support
    - Collaboration support
    - Other

7. *(Ver. B)* I would want to use AI tools for:
    - Programming / Coding

- Writing
- Automation
- Research
- Data analysis
- Brainstorming / Ideation
- Communication support
- Learning / Skill Development
- Design and visualization
- Decision support
- Collaboration support
- Other

Performance Expectancy

9. *(Ver. A)* Please indicate your level of agreement with the following statements:

    - I believe using AI tools is useful in my job.
    - I believe using AI tools helps me accomplish tasks more quickly.
    - I believe using AI tools increases my productivity at work.
    - I believe using AI tools improves my overall job performance.
    - I believe AI tools enhance the quality of my work.

9. *(Ver. B)* Please indicate your level of agreement with the following statements:

    - I believe using AI tools could be useful in my job.
    - I believe using AI tools could help me accomplish tasks more quickly.
    - I believe using AI tools could increase my productivity at work.
    - I believe using AI tools could improve my overall job performance.
    - I believe AI tools could enhance the quality of my work.

Effort Expectancy

11. *(Ver. A)* Please indicate your level of agreement with the following statements:

    - I believe learning to use AI tools is easy for me.
    - I believe interaction with AI tools is clear and understandable.
    - I believe AI tools are easy to use.
    - I believe it is easy to get AI tools to do what I want them to do.*
    - I believe I can easily become skillful at using AI tools.

11. *(Ver. B)* Please indicate your level of agreement with the following statements:

    - I believe learning to use AI tools could be easy for me.
    - I believe interaction with AI tools could be clear and understandable.
    - I believe AI tools could be easy to use.
    - I believe it could be easy to get AI tools to do what I want them to do.*
    - I believe I would be able to become skillful at using AI tools.

Social Influence

13. *(Ver. A)* Please indicate your level of agreement with the following statements:

    - People who are important to me at work think I should use AI tools.
    - My colleagues encourage me to use AI tools.
    - Management in my company supports the use of AI tools.
    - I feel pressure from others in the organization to use AI tools.*

13. *(Ver. B)* Please indicate your level of agreement with the following statements:

    - People who are important to me at work believe I should use AI tools.
    - My colleagues would encourage me to use AI tools.
    - Management in my company supports the use of AI tools.
    - I would feel pressure from others in the organization to use AI tools.*

Facilitating Conditions

15. *(Ver. A)* Please indicate your level of agreement with the following statements:

    - I believe I have access to the software needed to use AI tools.*
    - I believe I have the knowledge necessary to use AI tools.
    - I believe AI tools are compatible with other systems and software I use at work.*
    - If I have trouble using AI tools, I believe I can get help from others in the company.
    - I believe my company provides sufficient training and assistance for using AI tools.*

15. *(Ver. B)* Please indicate your level of agreement with the following statements:

    - I believe I have access to the software needed to use AI tools.*
    - I believe I have the knowledge necessary to use AI tools.
    - I believe AI tools could be compatible with other systems and software I use at work.*
    - If I have trouble using AI tools, I believe I can get help from others in the company.
    - I believe my company provides sufficient training and assistance for using AI tools.*

Hedonic Motivation

17. *(Ver. A)* Please indicate your level of agreement with the following statements:

    - I believe using AI tools is fun.
    - I believe using AI tools is entertaining.
    - I enjoy using AI tools as part of my work.
    - I believe using AI tools makes my work more interesting.

17. *(Ver. B)* Please indicate your level of agreement with the following statements:

    - I believe using AI tools could be fun.
    - I believe using AI tools could be entertaining.
    - I could enjoy using AI tools as part of my work.
    - I believe using AI tools could make my work more interesting.

Habit

19. *(Ver. A)* Please indicate your level of agreement with the following statements:

    - I use AI tools outside of work.
    - Using AI tools at work has become a habit for me.
    - I use AI tools automatically, without thinking about it.*
    - I would find it difficult to do my job without AI tools.

19. *(Ver. B)* Please indicate your level of agreement with the following statements:

    - I would use AI tools outside of work.
    - Using AI tools at work could become a habit for me.
    - I could use AI tools automatically, without thinking about it.*
    - I would find it difficult to do my job without AI tools.

Algorithmic Aversion

21. *(Ver. A)* Please indicate your level of agreement with the following statements:

    - I trust AI tools to perform their tasks.*
    - I feel comfortable relying on AI tools for important tasks.*
    - I believe AI tools provide accurate information.
    - I believe AI tools provide reliable information.
    - I prefer to rely on human judgment rather than on AI tools.*

21. *(Ver. B)* Please indicate your level of agreement with the following statements:

    - I could trust AI tools to perform their tasks.*
    - I would feel comfortable relying on AI tools for important tasks.*
    - I believe AI tools could provide accurate information.
    - I believe AI tools could provide reliable information.
    - I prefer to rely on human judgment rather than on AI tools.*

Organizational Trust

23. Please indicate your level of agreement with the following statements:

    - I trust that Nedap's AI use policies effectively protect sensitive data and my privacy.
    - I believe Nedap's guidelines ensure that AI tools are used in an ethical and responsible manner.
    - I have confidence that management provides proper oversight of AI algorithms to prevent unfair and biased outcomes.
    - I trust Nedap to handle and use AI training data in a way that respects privacy and security policies.
    - I am confident that the company will enforce its AI-related policies and address any misuse of AI tools promptly.

Open-ended Question

24. Do you have any experiences with AI tools at work that you would like to share?

Post-Survey Interview

25. Would you be open to joining a follow-up interview on this topic?

26. What is your email address and/or Slack name?

Note:

Ver.A refers to the questions given to participants when they choose 'Yes' in question 4

Ver.B refers to the questions given to participants when they choose 'No' in question 4

** These items were removed after PCA.*

Appendix B

Interview Procedure

Introduction (Approx. 5 minutes)

At the start of the interview, participants were welcomed and thanked for their participation. The purpose of the interview was explained, with emphasis on confidentiality and voluntary participation. Informed consent was obtained before proceeding.

Participants were briefly asked about:

- Their current role at Nedap
- The length of time they have worked at Nedap

General AI Use Context (Approx. 10 minutes)

To establish context, participants were asked open-ended questions about their general use of AI tools at work, including:

- Can you describe how you typically use AI tools in your daily work?
- Which AI tools or platforms do you use most frequently?
- What motivates you to use AI (e.g., efficiency, curiosity, workload reduction)?
- How integrated are these tools in your workflow?

Challenges and Misunderstandings (Approx. 15 minutes)

This section focused on difficulties, limitations, and critical experiences with AI tools:

- Have you experienced any errors or misunderstandings when using AI tools?
- Can you describe a situation where AI disrupted your workflow?
- How do you usually handle such situations?
- Do you feel confident in evaluating AI outputs for accuracy or relevance?
- Are there specific features or design aspects that make AI harder to use?

Perceived Outcomes and Value (Approx. 15 minutes)

Participants were asked to reflect on the outcomes and perceived value of AI use:

- Can you describe an instance where using AI helped you perform better or learn something new?
- In what ways has AI supported your creativity or skill development?
- Do you feel AI has affected your motivation or job satisfaction? If so, how?
- Have you changed the way you work because of AI?
- How has AI use influenced collaboration with colleagues?

Closing (Approx. 5 minutes)

The interview concluded with reflective and forward-looking questions:

- What would make your experience with AI tools more effective or enjoyable?
- Is there anything else you would like to add about AI use at Nedap?

Participants were thanked for their time, and the next steps of the research were briefly explained.

Appendix C

Qualitative Codebook

This appendix presents the codebook used for the qualitative analysis of the interview data.

Table C1

Qualitative Codebook

Code	Frequency
Accuracy improvement needed	2
AI errors	13
AI use case	
AI as a starting point	6
AI as a supportive tool	14
AI only uses for simple tasks	3
Automation	2
Brainstorming support	1
Design support	2
Language barrier support	4
Programming support	21
Technical support	1
Writing support	8
Ambiguity in communication with AI	6
Annoyed by AI behavior	3
Barrier to adoption	
AI unable to perform task	2
Cost of AI	1
Difficult to deep dive	1
Difficulty Keeping Up with AI Developments	2
Learning Curve	4
Team function does not support AI use	3
Benefits of using AI	
Benefit of using AI: Productivity improvement	4
Benefit of using AI: Time saving	11

Code	**Frequency**
Career background influence	3
Careful AI use	5
Change in work process	9
Colleague influence	10
Context importance	2
Creativity	4
Curiosity drive adoption	2
Customer Support	7
Dependence on AI	2
Difficulty Testing AI Output	1
Disruption from AI	3
Ease of Use	2
Environment concern	1
Hallucination in AI output	3
Higher-level task focus	1
Human in the Loop Importance	6
Interest toward AI	3
Job satisfaction	6
Knowledge sharing	8
Late adoption	1
Learning Strategy	6
Limitation of AI technology	1
Limited AI use outside work	1
Limited Tool Use	3
Lower product quality	1
Need for Advanced AI Training	4
Obligation to Use AI	1
Observability platform	2
Optimism about AI Future	1
Outcome Satisfaction	2

Code	**Frequency**
Output evaluation	18
Passive adoption	2
Peer pressure	3
Perceived training benefit	7
Policy training suggestion	1
Positivity in proactive adoption	5
Potential of AI in Data Analysis	2
Programming Tools/Language	2
Prompt Engineer	9
Proposed Improvement for AI Adoption	11
Rare AI Use	2
Recognition of typical AI behavior	5
Reduced enjoyment due to AI	2
Reject using AI for communication purposes	2
Reliability	5
Replace/Reduce peer communication	5
Role description	9
Scattered AI use	1
Second adopter	1
Self-sufficiency through AI	1
Simple introduction	2
Skepticism before adoption	2
Social Influence	10
Strong technical background	5
Struggle to start with new AI tools	5
Technical background limitation	7
Token limitation	2
Tool use	
ChatGPT/OpenAI use	18
Claude use	2

Code	Frequency
Copilot use	4
Cursor use	13
IntelliJ use	1
n8n	2
Tools comparison	2
Tools training	9
Trade-off in AI use	3
Trust in AI	5
Uncertainty in (some) AI usage	4
Unclear AI use context	1
Unexpected capability	2
User input importance	10
Work period	7

Appendix D

Prompt Coach User Interfaces

Figure D1

Start screen

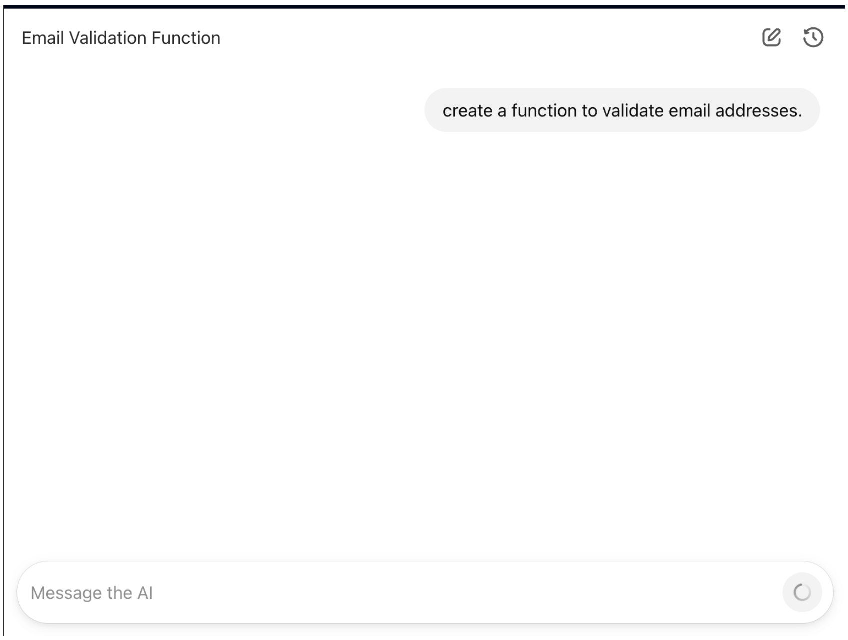

Figure D2

User enters initial prompt

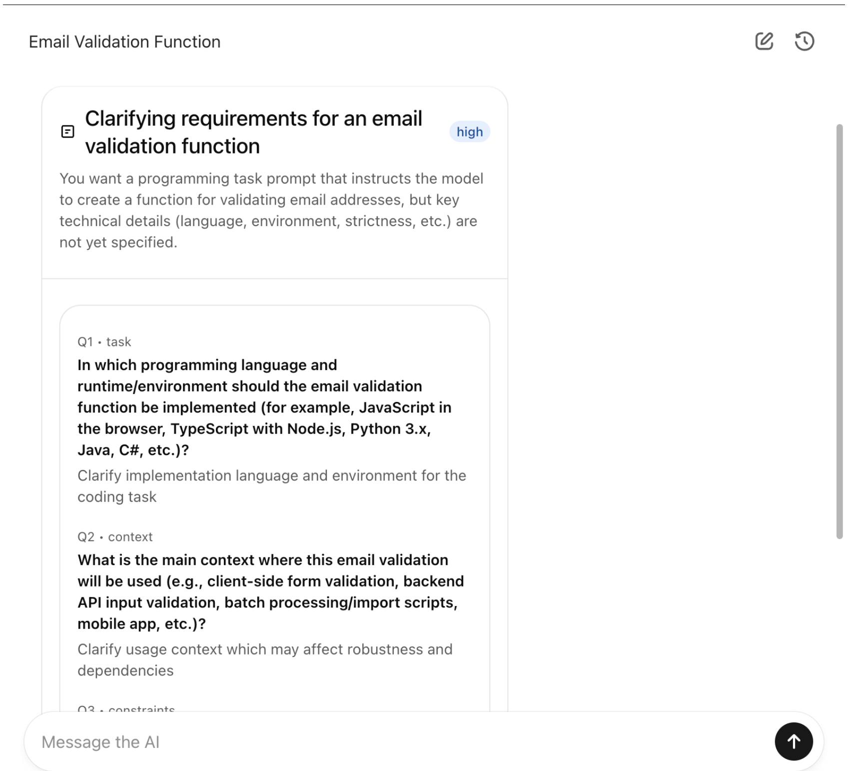

Figure D3

Clarifying questions generated

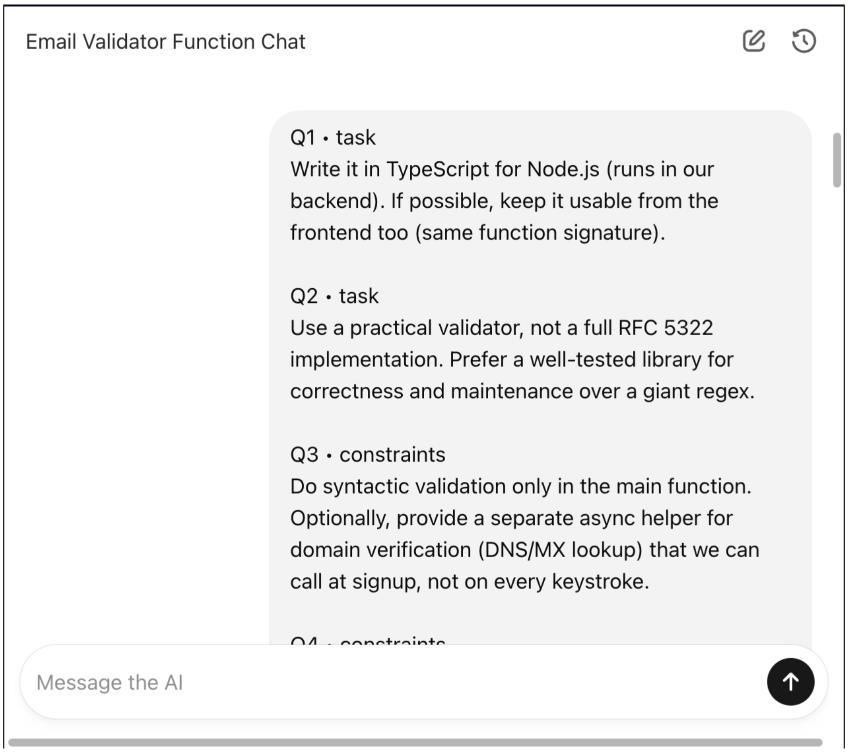

Figure D4

User answers the questions

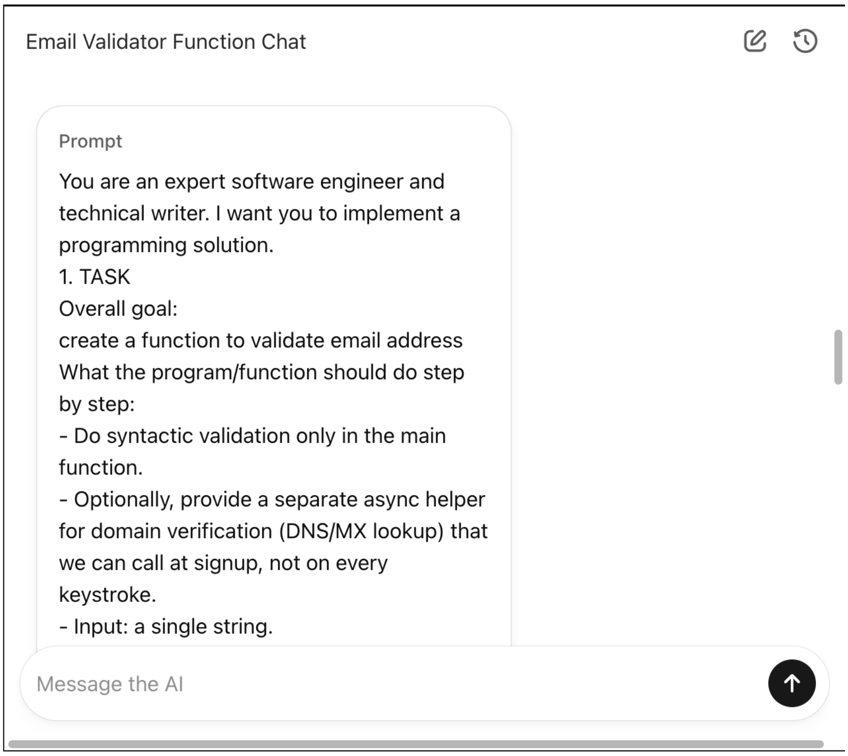

Figure D5

Prompt generated

Appendix E

The use of Artificial Intelligence (AI) in this research

During the preparation of this work, the author used the following AI tools:

Table E1

Summarize of used AI tools

Tool	**Purpose**
ChatGPT	Refine writing to fit with the academic tone.
	Search for literature.
	Assist with formulating the survey and interview procedures.
	Help creating prompt template.
NotebookLM	Summarize papers, books, and sources.
	Check for accuracy of citations.
Cursor + Claude	Debug code during data analysis.
	Generate and debug code for the intervention.
Grammarly	Check for grammar and structure errors in writing.

After using these tools/services, the author reviewed and edited the content as needed and takes full responsibility for the content of the work.

Declaration of academic integrity - M-COM Master Thesis

I herewith declare that my master thesis is the result of my own work and that materials regarding the works of others, contributing to my master thesis, have been correctly cited and/or acknowledged.

I furthermore declare that I have taken notice of the principles and procedures regarding research ethics and academic integrity as presented in the UT Student Charter and on the website of the BMS Examination Board, or as mentioned otherwise during the course of my studies.

I finally declare that below actions regarding research ethics and academic integrity have been followed through:

1. In the case human test subjects were involved for data collection, I have filed a request for ethical review and my request has been approved by the BMS Ethics Committee
2. I have safeguarded the transmission of research files and documents, using my personal folder on the secure university network drive (P:\bms\cw\theses) or other means of safe data transmission.
3. I have stored my final master thesis and (raw) research data on my personal university network folder (P:\bms\cw\theses) or made it otherwise digitally available to my supervisors.
4. I have uploaded my draft master thesis, prior to the "green-light" meeting, for a plagiarism / similarity check on the M-COM Master Thesis Canvas website and I have shared the plagiarism / similarity report with my supervisors prior to the "green-light" meeting.
5. In the case AI generated content has been used, an appendix has been added in which I explain where and how AI generated content has been used for my master thesis (see info on University of Twente website).

Student name and signature:

Student name: Xuan Binh Minh Nguyen

Signature: ____________________