Proceedings of the 7th African International Conference on Industrial Engineering and Operations Management
Cape Town, South Africa, May 13-15, 2026

Proceedings of the International Conference on Industrial Engineering and Operations Management

Publisher: IEOM Society International, USA DOI: 10.46254/AF07.20260016
Published: May 13, 2026

The Implementation of AI Assistants to Reduce Redundant Administrative Tasks in Team Operations

Tyron Ruben Jansen
Department of Industrial Engineering
Stellenbosch University
Stellenbosch, South Africa

Michelle Smit
Department of Industrial Engineering
Stellenbosch University
Stellenbosch, South Africa
michellesmit@sun.ac.za

Abstract

Administrative tasks occupy a substantial portion of engineers' working hours and are widely perceived as burdensome, stressful, and detrimental to productivity. This study investigates the key determinants influencing engineers' behavioural intention to adopt AI assistants to reduce administrative workload. Using a quantitative survey design grounded in an extended UTAUT model, the descriptive findings highlight both the operational strain of administrative work and the growing familiarity of AI assistants, particularly ChatGPT, which establishes a favourable foundation for adoption. The inferential findings show that the regression model demonstrates strong explanatory power. Performance expectancy emerged as the strongest and most significant predictor of adoption, reaffirming its central role in technology adoption among technical professionals. Social influence also had a meaningful and positive effect, indicating the importance of peer norms inn early adoption. Effort expectancy, perceived risk, and hedonic motivation were not significant, suggesting that engineers prioritise productivity benefits over usability concerns or perceived enjoyment when evaluating new digital tools.

Keywords
AI assistant; adoption; perception; behavioural intention

1. Introduction
Administrative work refers to essential organisational tasks that are deeply embedded in a business' daily operations (Breck, 2024). They refer to routine and redundant activities such as compiling meeting minutes, coordinating meetings, preparing reports, organising documents, and retrieving information. These activities tend to be prevalent across various sectors such as healthcare, education, finance, and engineering (Breck, 2024; Tiggelaar et al., 2023). Although they are important to a business' operations, they do not contribute to innovation, problem-solving, nor value creation (Tiggelaar et al., 2023). Consequently, given their importance, employees naturally tend to spend a significant portion of their day completing these tasks. Research has found that employees in the technology, media, and telecommunications sector spend nearly 30% more time on administrative tasks compared to other industries, despite being viewed as leaders in digital adoption (Brownridge et al., 2025). A similar trend is observed in the energy and industrial sectors, where 67% of employees express a preference for dedicating more of their time to performance-enhancing and innovative activities (Brownridge et al., 2025). In human resources, administrative duties consume as much as 57% of working time, while entrepreneurs devote approximately 36% of their weekly hours to tasks that could potentially be automated (Cole & Nooray, 2023; Lashbrooke, 2023). Consequently, redundant administrative tasks can reduce productivity and divert attention from an employees' core responsibilities.

Advancements in artificial intelligence (AI) offers an opportunity to address this challenge. In recent years, artificial intelligence (AI) has become the technological backbone of the Fourth Industrial Revolution (4IR), an era marked by the progressive integration of physical, digital, and biological domains that enable intelligent automation, interconnected systems, and large data-driven processes (Huynh et al., 2020; Sharma & Singh, 2020; Ziatdinov et al., 2024). AI is designed to replicate core human cognitive processes such as perception, learning, reasoning, and decision-making (Blumberg et al., 2024; Zirar et al., 2023). Among the most practical of these advancements are AI assistants (Zhang et al., 2024). AI assistants, also known as virtual or digital assistants, are intelligent applications designed to interact with users through conversational interfaces and perform tasks on their behalf (Hu et al., 2025; Nawaz, 2024; Oranye, 2024; Orpical, 2024). They appear in various forms including virtual chatbots, conversational agents, AI-powered personal assistants, and digital adoption platforms (Oranye, 2024) – with well-known examples such as Apple's Siri, Google Assistant, ChatGPT, and Google Gemini. Unlike conventional AI system or autonomous AI agents, AI assistants operate in response to a clearly defined problem or query and rely continuous user input to guide and sustain the interaction (Hu et al., 2025). Drawing on the information available to them, AI assistants can propose relevant insights, recommendations, or potential actions. They can also be adapted to more specialised tasks through various tuning methods that refine their behaviour without requiring full model retraining (Hu et al., 2025). Consequently, they are ideal AI tools that can be used to automate, streamline, or support repetitive administrative processes (Orpical, 2024). Therefore, their integration into team operations has the potential to reduce administrative burden and enhance both individual and team effectiveness.

However, successful implementation depends on whether employees are willing to integrate these tools into their daily workflow. Internal resistance often stems from concerns about job security, job complexity, trust, reliability, usability, usefulness, and performance expectations (Golgeci et al., 2025; Seeber et al., 2020; Shankar Babu et al., 2024). Although research on AI adoption is expanding, limited empirical evidence exists on the behavioural intention of engineers to adopt AI assistants specifically for reducing redundant administrative tasks.

This gap is problematic because administrative activities continue to constrain engineering teams by consuming a considerable amount of time and diverting attention from higher-value activities such as strategic planning, problem solving, and innovation. Without understanding the factors that can influence engineers' adoption intentions, organisations may invest in AI tools that fail to make an impact on their operations. Therefore, to capture this dynamic, this study employs an extended Unified Theory of Acceptance of Acceptance and Use of Technology (UTAUT) model to understand engineers' attitudes towards implementing AI assistants to reduce redundant administrative tasks in team operations.

1.1 Objectives

The proposed research study aims to investigate the factors that influence engineer's behavioural intention to adopt AI assistants to reduce redundant administrative tasks in team operations. Therefore, the objectives of this study are as follows:

- To identify and synthesise the key factors influencing the adoption of AI assistants in team environments.
- To apply an extended UTAUT framework to analyse how theoretical constructs, namely performance expectancy (PE), effort expectancy (EE), social influence (SI), perceived risks (PR), and hedonic motivation (HM), affect engineers' behavioural intention (BI) to adopt AI assistants.
- To explore engineers' perceptions of AI assistants of redundant administrative tasks and evaluate the perceived impact that AI assistants may have on reducing this workload.

2. Literature Review

2.1 Understanding administrative tasks

Administrative tasks form a core component of organisational operations, encompassing planning, documenting, coordinating, and reporting activities that ensure continuity and accountability (Pennathur et al., 2024). Although essential, these tasks are predominantly routine, rule-based, and time-intensive, offering limited technical or strategic value (Frank & Frenette, 2021). As a result, they frequently contribute to cognitive strain and disengagement among engineers whose expertise is better aligned with analytical and problem-solving activities (Tiggelaar et al., 2023).
The concept of "administrative burden" captures the negative experience associated with fulfilling these procedural requirements (Hattke et al., 2020; Herd & Moynihan, 2018; Tiggelaar et al., 2023). In engineering environments—especially those governed by stringent regulatory standards—administrative burden is amplified by extensive

documentation demands that divert attention from design, optimisation, and innovation. This diversion reduces autonomy and fosters feelings of powerlessness and meaninglessness, ultimately eroding motivation, concentration, job satisfaction, and project quality.

Industry evidence reinforces these concerns. Recent reports show that professionals spend more than a third of their working hours on administrative or low-value tasks, limiting time for strategic thinking, mentorship, and technical development (Deloitte, 2025). These patterns constrain organisational growth and intensify stress among engineering professionals.

Therefore, understanding administrative burden is essential for identifying where AI assistants can provide meaningful relief by automating repetitive processes that undermine technical engagement and productivity.

2.2 Automation and digitalisation of administrative tasks

Automation and digitalisation have become central to how engineering organisations streamline operations, improve workflow reliability, and implement strategies to maintain a competitive advantage. According to Parycek et al. (2024), automation operates along a continuum that ranges from task-level assistance systems that support employees, to partial automation where specific procedural steps are executed autonomously, and finally to full automation of structured workflows. This layered approach allows engineering teams to incrementally digitalise administrative procedures and gradually introduce automation into workflows without overwhelming employees. However, the extent to which automation can be embedded into systems is highly dependent on an organisation's AI infrastructure and the maturity of its digital ecosystem (Yin et al., 2024).

For engineering teams, particularly those who are characterised by complex projects, strict compliance requestions, and high documentation demands, reducing time spent on administrative tasks is essential for allowing engineers to focus on core technical work. Brownridge et al. (2025) argue that minimising the volume of non-value-adding activities such as administrative tasks and increasing engagement in value-adding activities are critical for improving organisational efficiency and employee well-being. While it is neither practical nor desirable to eliminate administrative responsibilities entirely, many organisations are turning to digital tools and automation technologies to streamline and optimise these tasks. Automation can offload repetitive, rule-based administrative tasks to digital systems, thus allowing engineers to redirect their efforts on their core responsibilities (Brownridge et al., 2025; Zirar et al., 2023).

Among these emerging technologies, AI-driven assistants have proven effective in addressing administrative inefficiencies. Yin et al. (2024) report that over 80% of large organisations have adopted AI tools across various operational functions, with many deploying AI assistants to support and manage routine work. These systems employ machine learning (ML), natural language processing (NLP), and data analytics to interpret user queries and respond to cues (Yin et al., 2024). Although AI assistants can handle increasingly complex and context-sensitive tasks, they remain limited in their capacity for creative reasoning and innovative thinking, aspects which are inherent to human cognition. Nevertheless, automating repetitive and time-consuming administrative tasks can reduce cognitive and emotional strain on engineers, thereby lessening administrative burden, and enabling them to sustain longer periods of focus on innovation, collaboration, and strategic problem-solving (Brownridge et al., 2025). Jarrahi (2018) highlights that automation fosters human-AI symbiosis where AI systems complement human strengths rather than replace them. In engineering contexts, this collaborative relationship enhances productivity by allowing AI assistants to manage structured administrative demands while engineers apply their expertise to complex technical issues. Therefore, integrating automation and digitalisation into engineering team operations should not be viewed merely as a technological enhancement. Instead, it represents a strategic enabler that establishes the conditions under which AI assistants can reduce redundant administrative tasks and improve overall team performance (Rožman et al., 2023; Yin et al., 2024).

2.3 AI assistants: Capabilities, characteristics, and limitations

The rapid development of AI has led to two closely related yet distinct classes of systems, namely AI assistants and AI agents (Hu et al., 2025). Although they stem from similar underlying technologies, their roles and levels of autonomy differ. AI assistants are intelligent software applications that use natural processing to help users access information, complete tasks, and navigate workflows (Hu et al., 2025; Oranye, 2024; Yin et al., 2024). Early assistants relied on rule-based instructions and predefined commands, but modern-day assistants are built on machine learning models, most commonly large language models (LLM), which form part of broader foundation models such as IBM Granite, Llama, or OpenAI models (Hu et al., 2025; Yin et al., 2024). These models enable assistants to interpret user prompts, generate relevant information or recommendations, and support routine operational activities in organisations, including ask automation, information retrieval, and basic data analysis (Hu et al., 2025; Nawaz, 2024; Takyar, 2025). AI assistants typically operate through conversational interfaces, whether text-based or voice-enabled, and many integrate with external applications through application programming interfaces (API's), which allows one program to share information with another (Goodwin, 2025), to execute actions on the user's behalf. Although they require explicit prompts to act and do not learn continuously outside developer-driven updates, some assistants can maintain short-term context or use built-in memory features to provide more personalised interactions (Hu et al., 2025). Well-known examples, such as Siri, Alexa, Google Assistant, Microsoft Copilot, and ChatGPT, illustrate how these systems combine natural language processing with tool-use capabilities to streamline repetitive tasks and improve user efficiency.

Conversely, an AI agent is an autonomous system that is capable of independently pursing a user-defined goal by designing and executing its own workflow, drawing on advanced machine learning, decision-making, and tool-use capabilities (Hu et al., 2025; Nawaz, 2024) . Unlike AI assistants, which depend on continuous prompts, AI agents can operate after an initial instruction by analysing a problem, breaking it into subtasks, and selecting the appropriate actions or tools to complete the task (Hu et al., 2025). Their behaviour extends beyond natural-language interaction and includes reasoning, problem-solving, interacting with external environments, and integrating with connected systems to perform multi-step processes (Hu et al., 2025; Nawaz, 2024). Modern agents often leverage LLM to interpret inputs, plan actions, and coordinate across applications, while features such as persistent memory, adaptive learning, and task chaining allow them to refine their performance over time and manage complex workflows with minimal human intervention. This combination of autonomy, connectivity, and goal-directed action makes AI agents suitable or sophisticated organisational tasks that require independent assessment, coordination, and execution (Hu et al., 2025; Nawaz, 2024).

2.4 AI assistant implementation challenges

Employee and organisational resistance to AI is a well-documented barrier to successful implementation. Recent integrative work conceptualises AI resistance as a multi-dimensional phenomenon rooted in fear, perceived inefficacy, and antipathy toward AI and driven by cognitive mechanisms such as mistrust, existential questioning, and technological reflection (Golgeci et al., 2025). These mechanisms operate in a recursive feedback loop with initial unease or uncertainty about AI can trigger mistrust, which in turn amplifies existential doubts about work identity and prompts deeper reflection that can harden resistance unless addressed (Golgeci et al., 2025).

At an individual level, resistance is shaped by fears of job loss, perceived loss of control, technostress, and algorithmic aversion (Golgeci et al., 2025). Studies highlight that AI's relative "black box" autonomy, ethical concerns such as bias, accountability, and privacy, and the rate of change intensify feelings of insecurity and mistrust, which predict avoidance behaviours and reluctance to engage with AI tools (Golgeci et al., 2025; Taofeek et al., 2024). Additionally, based on the adoption models such as the TAM and UTAUT, empirical reviews show trust, perceived usefulness, and effort expectancy remain strong predictors of willingness to use AI. Consequently, when the results for these indicators are low, resistance rises (Bryan & Zuva, 2021; Gansser & Reich, 2021; Taherdoost et al., 2024).

At the organisational level, structural and cultural barriers play a crucial role. Resistance can emerge from security and compliance issues, poor digital infrastructure, weak leadership communication, and misalignment between departments (Anaya et al., 2024; Rožman et al., 2023). When these factors are not proactively addressed, they can fuel scepticism and slow the pace of adoption. Small and medium-sized enterprises (SMEs) face these challenges more acutely due to limited resources, technical skills, and infrastructure constraints, making resistance more likely and even harder to mitigate (Schwaeke et al., 2024). In such cases, resistance is often not opposition to AI itself but rather a manifestation of organisational unpreparedness and anxiety about capability gaps.

Resistance to AI also has a social and institutional dimension (Golgeci et al., 2025). Broader societal debates about AI ethics, regulation, and the legitimacy of algorithmic decision-making often shape employee perceptions within the workplace. In some cases, resistance has escalated beyond individual reluctance and led to protests movements and public pushback against perceived threats of automation (Golgeci et al., 2025). This reaction is frequently underpinned by misconceptions that AI is designed to replace human labour entirely, overlooking its potential to complement and enhance human work. Fear of job displacement remains a significant hurdle for any organisation to overcome (Golgeci et al., 2025; Seeber et al., 2020; Taofeek et al., 2024). However, much of this anxiety stem from misunderstandings or the exaggerated perceptions of AI's true capabilities.

As noted by (Babu & Banana, 2024), there are key fundamental differences between human and artificial intelligence. AI lacks the fluidity, flexibility, self-awareness, consciousness, and emotional intelligence that characterise human cognition. While AI excels at pattern recognition and structured problem-solving, it lacks creativity and empathy. Consequently, rather than replacing humans, AI technologies often redefine work by automating routine tasks and creating new roles that combine technical expertise with soft skills such as critical thinking, communication, and adaptability (Sengodan, 2024). The key to overcoming resistance lies in understanding and communicating its true capabilities and limitations and proactively prepare the workforce by investing in comprehensive training programs that will equip employees with the necessary skills to thrive and meet evolving demands of the future AI-driven job market.

2.5 Models of technology adoption

2.5.1 Diffusion of Innovations theory

The DOI theory developed my Everett Rogers is built upon two key concepts: diffusion and innovation. Understanding each concept independently provides a framework for understanding how new ideas and technologies spread within a social system.

Diffusion is the process by which an innovation is communicated over time among members of a specific social system (Rogers, 1995). Rogers (1995) describes diffusion as a distinct form of communication because it transmits new ideas. Diffusion enables the exchange of information that can either challenge or expand existing practices. Through this process, participants share knowledge and experience to achieve mutual understanding or to develop differing interpretations (García-Avilés, 2020). Consequently, communication in diffusion may lead to either convergence or divergence, depending on whether individuals; perceptions become more aligned or distinct during their interactions (Rogers, 1995).

Innovation is defined as an idea, practice, or object perceived as new by an individual or group (Rogers, 1995). The emphasis is on perceived newness rather than objective novelty. According to Rogers (1995), an idea may have existed previously, but if an individual has not yet formed an opinion about it or decided to adopt or reject it, it remains an innovation from that individual's perspective. The newness of an innovation can be described in terms of knowledge, referring to awareness of its existence; persuasion, involving the formation of an attitude towards it; and decision, which entails choosing to adopt or reject the innovation.

Therefore, the DOI theory aims to explain the processes by which individuals decide whether to adopt or reject a particular innovation (García-Avilés, 2020). The diffusion process is often illustrated using an S-shaped curve and depicts the cumulative number of adopters over time.

2.5.2 Technology Adoption Life Cycle (TALC)

The Technology Adoption Life Cycle (TALC) builds on the DOI theory by extending its principles to the commercial and practical domains of technological products. TALP describes the progression of new technologies through the market by illustrating how distinct consumer categories adopt innovations over time (Moore, 1991). While the DOI theory centres on communication, perceived novelty, and adoption rates, the TALC focuses on the behavioural and psychological distinctions among adopter groups and the challenges associated with transitioning into the mainstream market (Moore, 1991).

The TALC is commonly depicted as a bell-shaped curve divided into five adopter categories: innovators, early adopters, early majority, late majority, and laggards.

2.5.3 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a framework that explains how users develop perceptions to new technology and how these perceptions influence their willingness to adopt it (Na et al., 2022). Unlike the Technology Adoption Life Cycle that focuses on a group of individuals, the TAM focuses on each individual and their attitude towards new technology. First introduced by Davis in 1989, the model posits that two core perceptions namely perceived usefulness (PU) and perceived ease of use (PEOU) to determine users' behavioural intention to use a technology (Na et al., 2022). PU reflects the extent to which an individual believes that a technology will enhance job performance, while PEOU denotes the degree to which using the technology is free of effort (Na et al., 2022). When users perceive a technology as both useful and easy to use, their attitude toward adoption becomes more favourable, increasing the likelihood of actual usage. Conversely, when users perceive a technology as useless and difficult to use, their attitude toward adoption is compromised and significantly decreases the probability of actual usage.

2.5.4 Unified Theory of Acceptance and Use of Technology (UTAUT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a framework that explains how individuals adopt and utilise technology (Marikyan & Papagiannidis, 2023). At its core, the model states that an individual's actual use of a technology is directly influenced by their behavioural intention.

the UTAUT model identifies four key constructs that influence an individual's acceptance and use of a new technology i.e. performance expectancy, effort expectancy, social influence, and facilitating conditions. Performance expectancy refers to the extent to which an individual believes that using the system will lead to improvements in their job performance. This corresponds with the TAM and essentially represent the perceived usefulness of the technology. Effort expectancy captures the perceived ease of use associated with the system. This too, corresponds with the TAM and evaluates how simply and user-friendly the individual finds its to interact the technology. Social influences refer to the perceived pressure or encouragement from other individuals or groups that can affect the user's decision to adopt the technology (Marikyan & Papagiannidis, 2023). Facilitating conditions represent the individual's belief that the necessary organisational and technical infrastructure is in place to support the effective use of the new technology. This includes access to training, assistance, resources, etc. Behavioural intention describes the individual's internal motivation or subjective likelihood that they will engage with and continue to use the technology in the future.

2.5.5 Task-Technology Fit (TTF)

The Task-Technology Fit (TTF) theory examines how well a technology aligns with the requirements of a particular task. Muchenje & Seppänen (2023) describes it as the degree to which a technology enables individuals to perform their work effectively. According to Spies et al. (2020), the TTF provides a framework for quantifying the effectiveness of technology in a system by analysing the interaction between technological capabilities and the specific tasks they are intended to support. The theory posits that a strong alignment, or fit, between a task and the technology used to execute it leads to improved performance outcomes (Jeyaraj, 2022). In addition to this, Howard & Rose (2019) observe that the relationship between tasks and technologies is often synergistic, such that their complementarity produces performance improvements greater than the sum of their individual contributions. Conversely, when technology does not align with the demands of a task, users may resist or avoid using it altogether (Muchenje & Seppänen, 2023). This highlights the critical importance of achieving balance between task needs and technological design.

TTF is frequently examined in relation to several associated constructs, including performance, user reactions, utility, perceived utility, and utilisation (Howard & Rose, 2019). These constructs are often mistakenly conflated with TTF itself. However, they do not represent dimensions of the theory but rather the outcomes that emerge when a technology effectively aligns with the requirements of a task (Howard & Rose, 2019).

2.5.6 Technology-Organisation-Environment (TOE) framework

The TOE framework provides a comprehensive model for examining the determinants that shape an organisation's decision to adopt and integrate new technologies (Baker, 2012). It offers a holistic view from an organisational perspective by acknowledging that technological adoption does not occur in isolation but rather through the dynamic interaction among technology, internal organisational factors, and external environmental influences (Neumann et al., 2024; Taherdoost et al., 2024).

The technological component pertains to the traits and perceived qualities of the technology being evaluated (Taherdoost et al., 2024). It entails evaluating criteria such as complexity, compatibility, and trialability (Taherdoost et al., 2024). The organisational component addresses the internal attributes that influence an organisation's capacity and readiness to adopt new technologies (Taherdoost et al., 2024). It encompasses structural characteristics, organisational culture, and readiness for change (Taherdoost et al., 2024). The environmental component examines the external factors that impact an organisation's technology adoption choices (Na et al., 2022). This encompasses the wider socioeconomic, political, and legal contexts in which the organisation functions (Taherdoost et al., 2024).

2.5.7 Technology Readiness Index (TRI)

The TRI is a conceptual framework designed to assess individuals' inclination to adopt and utilise new technology (Pires et al., 2023). It expands on the TAM by highlighting the psychological enablers and barriers that influence user perceptions (Nugroho & Fajar, 2017).

The framework has four fundamental dimensions, namely optimism, innovativeness, discomfort, and insecurity (Nugroho & Fajar, 2017). Optimism refers to the extent to which individuals have favourable expectancies regarding the potential of technology and its benefits. Innovativeness denotes an individual's receptiveness to experimentation and early acceptance of emerging technology. Conversely, discomfort refers to feelings of uncertainty and unease, or a lack of control in technological interactions, whist insecurity incorporates concerns about privacy, reliability, and dependence on technology (Nugroho & Fajar, 2017).

The two initial dimensions, namely optimism and innovativeness, act as contributors, enhancing the willingness to embrace new technology. In contrast, discomfort and insecurity serve as inhibitors, undermining users' motivation or confidence to utilise technologies. Pires et al. (2023) proposed an additional dimension to the framework, complexity, which assesses the perceived difficulty in understanding or utilising technology efficiently. This recommended dimension provides a broader perspective on the framework by recognising that readiness is influenced not only by attitude, but also by perceived competence and confidence in handling technology systems (Pires et al., 2023).

3. Proposed Model

The proposed model will incorporate the constructs of the UTAUT model to gain insight into individuals' perceptions of implementing AI to reduce redundant administrative tasks in team operations but also consider the associated perceived risks (PR) and hedonic motivations (HM). The perceived risks (PR) will entail concerns on whether the information provided by AI assistants can be trusted and whether it could potentially threaten privacy and confidential data. Hedonic motivation (HM) reflects the intrinsic enjoyment a user derives from interacting with a technology (Gansser & Reich, 2021). Facilitating conditions (FC) is excluded from the model as it predicts use behaviour and not behavioural intention. This specific construct varies widely across workplaces and is not within the user's control. Furthermore, the moderators i.e. age, gender, experience, and voluntariness of use, is excluded from the model as their inclusion would only add complexity without contributing meaningfully and could potentially produce inconsistent results across studies (Figure 1).

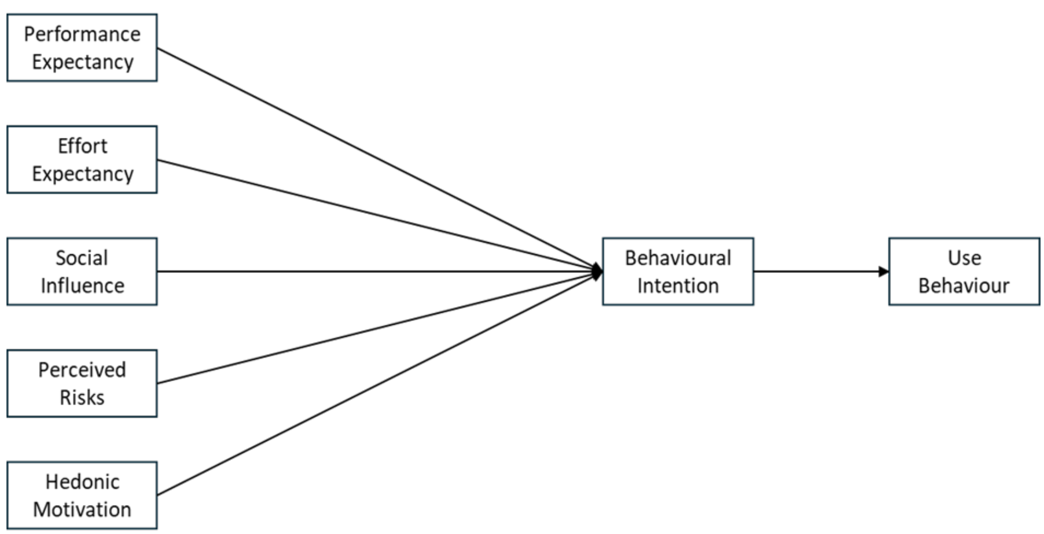

Figure 1: The proposed UTAUT model to include PR and HM

From the model shown above, the following hypothesis are developed:

- H1: Performance expectancy positively influences engineers' behavioural intention to use AI assistants.
- H2: Effort expectancy positively influences engineers' behavioural intention to use AI assistants.
- H3: Social influence positively influences engineers' behavioural intention to use AI assistants.
- H4: Perceived risk negatively influences engineers' behavioural intention to use AI assistants.
- H5: Hedonic motivation positively influences engineers' behavioural intention to use AI assistants.

The proposed model is based on previous studies that have successfully extended the UTAUT model by incorporating perceived risk, hedonic motivations, and other related constructs to improve its explanatory capacity. These studies

provide both the theoretical and empirical justification for the model adopted in this research, which focuses on the implementation of AI assistants to reduce redundant administrative tasks in team operations.
Lee & Song (2013) investigated the impact of trust and perceived risk on technology acceptance by incorporating these constructs into the UTAUT model. Their findings revealed that PR negatively affects behavioural intention, whereas trust exerts a mitigating effect that can alleviate the negative impact of risk perceptions. In their study, PE and SI remained significant predictors of intention to use, confirming the robustness of UTAUT's core constructs. This evidence reinforces the inclusion of PR in the current model as users may experience uncertainty or hesitation when AI assistants are entrusted with administrative tasks that involve sensitive or confidential information (Lee & Song, 2013).
Gansser & Reich (2021) also proposed an extension of the UTAUT2 model in their study on AI acceptance. Their findings showed that the inclusion of psychological and contextual variables such as perceived safety, hedonic motivation, and personal innovativeness, improved the model's ability to predict user acceptance. This evidence supports the inclusion of HM in the current model and showcases how the flexibility of UTAUT base model that can be adapted to different technological settings.

4. Research Method or Approach

The study employed a quantitative survey to collect structured and comparable data on engineers' perceptions of AI assistants. This approach aligned with the study's focus on measurable constructs from the UTAUT framework. Closed-ended questions were used to minimise ambiguity, enhance objectivity, and enable statistical analysis, while avoiding the interpretive limitations and resource demands associated with qualitative surveys.

The target population consisted of South African engineers holding BEng, BScEng, or BTech qualifications, as these professionals routinely engage in administrative tasks that AI assistants could potentially reduce. A non-probability convenience sampling strategy was used due to the exploratory nature of the study. Sixty engineers completed the online questionnaire, exceeding the minimum requirement determined by the ten-times rule for PLS-SEM. The survey comprised 30 items, including demographic questions, administrative workload and AI familiarity measures, and Likert-scale statements assessing performance expectancy, effort expectancy, social influence, perceived risk, hedonic motivation, and behavioural intention. This design ensured alignment with the conceptual framework and facilitated reliable insight into engineers' readiness to adopt AI assistants.

5. Results

5.1 Descriptive Results

A considerable percentage of respondents have expressed that they allocate a substantial amount of their workday to administrative tasks with 10% dedicating less than 1 hours daily, 38.33% spending between 1-2 hours daily, and 51.67% exceeding 2 hours per day.Although administrative tasks have been deemed essential to daily operations, the majority of respondents concurred that administrative tasks tend to have an adverse effect on their productivity, with 56.67% in agreement and 20% in strong agreement. Furthermore, 28.33% agreed and 20% strongly agreed that they experience frustration and become overwhelmed when dealing with administrative tasks. Consequently, these findings suggest that administrative tasks have become a significant source of stress and inefficiency, further supporting the need to investigate the potential role of AI assistants in optimising these operations.

The survey also evaluated the level of awareness and prior use of AI assistants among the respondents. The list of AI assistants in the survey included ChatGPT, Microsoft Copilot, Notion AI, Todoist, ClickUp AI, Googe Workspace, Asana AI, Clara, and OtterAI. Figure 2 below visually indicates the familiarity of different AI assistants among the respondents.

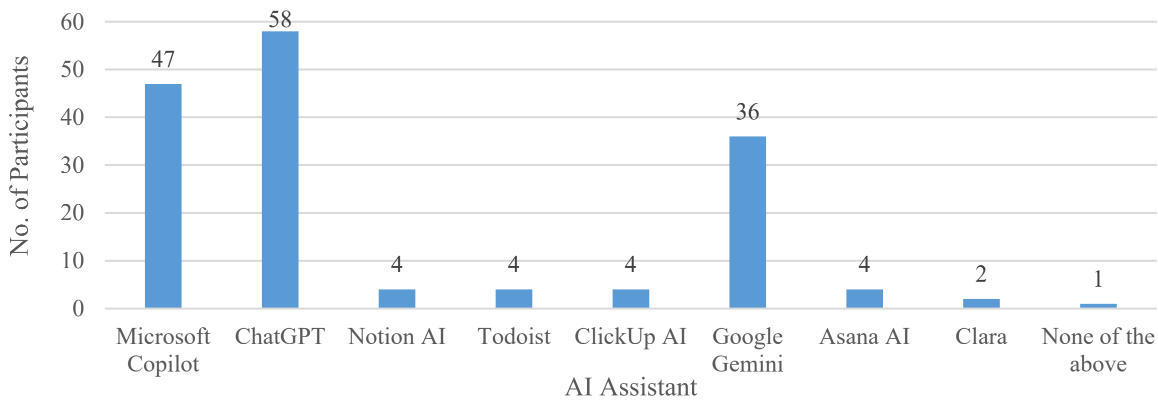

Figure 2: Level of Familiarity of Different Types of AI Assistants

The results revealed that 98.33% of respondents were aware or familiar with at least one of the specified AI assistants. Among them, ChatGPT emerged as the most recognised, with 96.66% of respondents indicating awareness, followed by Microsoft Copilot with 78.33%, and Google Gemini with 60% of respondents. These findings are consistent with literature and how the introduction of ChatGPT marked a pivotal turning point in the evolution of generative AI (Sætra, 2023; Hacker et al. 2023). The unprecedented success and accessibility of ChatGPT not only popularised LLM but also sparked the rapid development of similar generative AI assistants such as Microsoft Copilot and Google Gemini. This phenomenon reflects the diffusion of innovation effect whereby a breakthrough innovation acts as a catalyst for subsequent competitive products. Consequently, it is not unexpected that ChatGPT is the most recognised AI assistant among respondents. Its early market launch, extensive media coverage, and integration in everyday life have set it ahead of its competitors.

5.2 Inferential Analysis

Model fit and explanatory power

Table 1 below provides insight into the model fit and its explanatory power. The regression model demonstrates a strong level of explanatory power. As shown in Table 1 above, the model yields an R value of 0.776, indicating a strong correlation between the set of independent key constructs (PE, EE, SI, PR, and HM) and the dependent behavioural intention (BI) construct. The R^2 value of 0.603 shows that nearly 60.3% of the variance in BI is accounted for the five predictors i.e. PE, EE, SI, PR, and HM. The adjusted R^2 of 0.566 further confirms that the model remains robust even after adjusting for the number of predictors relative to the sample size of 60 engineers. Therefore, based on these results, the model fit indicates that the chosen constructs collectively offer a meaningful and statistically defensible explanation of engineers' behavioural intention to adopt AI assistants.

Table 1: Regression Statistics

Multiple R	0.776
R Square	0.603
Adjusted R Square	0.566
Standard Error	0.659
Observations	60

ANOVA Analysis

Table 2 below provides insight into the accuracy model. The ANOVA results provide additional confirmation that the regression model is statistically significant. The F-statistic of 16.373, with a corresponding p-value of 8.297 x 10-10 is far below the 0.05 threshold. This indicates that the model accurately predicts the behavioural intention of engineers to implement AI assistants to reduce redundant administrative tasks in their team operations.

Table 2. ANOVA Analysis

	df	SS	MS	F	Significance F
Regression	5	35.550	7.110	16.373	8.297E-10
Residual	54	23.450	0.434		
Total	59	59			

Regression coefficients and significance of predictors
Table 3 below provides insight into the statistical significance of each construct. As seen in Table 3 above, PE emerges as the strongest and most statistically significant predictor of behavioural intention. A coefficient of 0.529 indicates a large positive effect. Therefore, as engineers increasingly believe that AI assistants will improve their efficiency and performance, their intention to use these tools rises. Additionally, the high t-statistic and extremely low p-value confirm the reliability of this effect, and the confidence interval lies entirely above zero. Therefore, these findings strongly validate H1, which predicted a positive relationship. This outcome is consistent with decades of technology acceptance and diffusion research showing PE as the dominant determinant of BI especially in technical and professional domains where productivity gains are prioritised (de Bruin, 2020; Gansser & Reich, 2021; Kenesei et al., 2025; Rogers, 1995).

Conversely, EE exhibits a rather small coefficient and a non-significant effect. The extremely low t-value indicates that ease of use does not meaningfully influence engineers' intention to implement and adopt AI assistants. Furthermore, because the confidence interval spans zero and the p-value is substantially above the 0.05 threshold, H2 is not supported. It is likely that because engineers possess strong technical competence and are accustomed to adopting new digital tools, effort expectancy is not a decisive factor in shaping their behavioural intention. Therefore, the effect of EE diminishes as users become more technologically competent (Venkatesh et al., 2003; Venkatesh & Bala, 2008).

Table 3. Regression Coefficients

	Coefficient	Standard Error	t-Statistic	P-value	Lower 95%	Upper 95%
Intercept	2,899E-16	0,085	3,408E-15	1	-0,171	0,171
PE	0,529	0,110	4,819	1,213E-05	0,309	0,750
EE	0,017	0,096	0,174	0,862	-0,176	0,210
SI	0,274	0,098	2,790	0,007	0,077	0,472
PR	-0,074	0,102	-0,722	0,473	-0,279	0,131
HM	0,162	0,114	1,419	0,162	-0,067	0,391

SI is a moderate but statistically significant predictor of behavioural intention. The coefficient of 0.274 indicates that aspects such as peer behaviour, managerial expectations, and organisational norms meaningfully shape engineers' willingness to adopt AI assistants. Additionally, the t-statistic of 2.790 and the entirely positive confidence interval confirm this effect's reliability. Therefore, the significant positive association provides empirical support for H3. This is consistent with UTAUT which highlights that SI is particularly influential during early adoption stages or when technologies are novel, uncertain, or not yet institutionalised (Venkatesh et al., 2003), conditions that accurately describe AI assistant adoption in many engineering environments.

As seen in Table 3, PR has a negative coefficient which is consistent with theoretical expectations, but the effect is statistically insignificant. The low t-value, large p-value, and broad confidence interval spanning zero, indicate that perceived risk does not significantly deter engineers from intending to use AI assistants. Therefore, H4 is not supported. Consequently, this suggests that concerns about data privacy errors are not decisive factors for engineering professionals. This may be because engineers are dependent on their organisation's data protection structures to mitigate any data breaching concerns.

Finally, HM exhibits a positive but statistically non-significant effect. Although some engineers may experience enjoyment and satisfaction when using AI assistants, this does not appear to significantly influence their behavioural intention. The confidence interval crosses zero and the p-value exceeds the threshold for significance, thus leading to the conclusion that H5 is not supported.

6. Conclusions and Recommendations

This research a comprehensive analysis of the empirical findings of the study and demonstrated how both descriptive and inferential results aligned with the study's research objectives and questions. The descriptive analysis reveals that administrative tasks occupy a significant portion of engineers' daily working hours and are perceived as a burden, source of stress, and productivity inhibitor. These insights emphasise not only the operational significance of administrative work, but also the increasing need for AI assistants that can alleviate these pressures. Furthermore, the familiarity with AI assistants, most notably ChatGPT, highlights the extent to which AI has already diffused into professional awareness, thus establishing a favourable foundation for future adoption.

Finally, the inferential analysis offered deeper insight into the determinants influencing engineers' behavioural intention to adopt AI assistants. The regression model demonstrated strong explanatory power, indicating that the chosen UTAUT-based constructs collectively provide a robust explanation for adoption behaviour. Among these predictors, PE emerged as the most influential and statistically significant factor, reinforcing the long-standing empirical evidence that PE remains the primary driver of technology adoption in technical environments. SI also showed a meaningful and significant effect which indicates the important role of peer norms in shaping early adoption decisions. Conversely, EE, PR, and HM did not exhibit significant effects, suggesting that usability concerns, risk perceptions, and enjoyment are less decisive for engineering professionals who are already accustomed to adopting complex digital tools.

Future research may benefit from expanding on the proposed UTAUT model to include other the moderating variables. This will highlight whether engineers from different age groups, experience, and genders perceive the adoption of AI assistants differently. Additionally, another recommendation will be to incorporate a mixed methods approach i.e. a combination of qualitative and quantitative which may uncover more behavioural and organisational dynamics that cannot be fully captured through quantitative surveys.

References

Anaya, L., Braizat, A., & Al-Ani, R. Implementing AI-based Chatbot: Benefits and Challenges. *Procedia Computer Science, 239*, 1173–1179, 2024. https://doi.org/10.1016/j.procs.2024.06.284

Babu, S., & Banana, K. A STUDY ON NARROW ARTIFICIAL INTELLIGENCE-AN OVERVIEW. *International Journal of Engineering Science and Advanced Technology (IJESAT), 24*, 2024. www.ijesat.com

Baker, J. The Technology–Organization–Environment Framework (pp. 231–245), 2012. https://doi.org/10.1007/978-1-4419-6108-2_12

Blumberg, S., Chui, M., Yee, L., Javanmardian, K., Singla, A., Smaje, K., & Sukharevsky, A. What is AI (artificial intelligence)? *McKinsey & Company*, 2024. https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-ai#/

Breck, C. Administrivia: Reconsidering the Engineering and Management Tracks, July 28, 2024. https://blog.colinbreck.com/administrivia-reconsidering-the-engineering-and-management-tracks/

Brownridge, J., Wilp, A., Noble, L., & Beckett, C. The Digital Workplace Productivity+ Series: Part 4. *Deloitte*, February 7, 2025. https://www2.deloitte.com/us/en/blog/human-capital-blog/2025/enhanced-employee-productivity-with-generative-ai-tools-in-digital-workplace.html

Bryan, J. D., & Zuva, T. A Review on TAM and TOE Framework Progression and How These Models Integrate. *Advances in Science, Technology and Engineering Systems Journal, 6*(3), 137–145, 2021. https://doi.org/10.25046/aj060316

Cole, G., & Nooray, M. Modernizing HR: Design Thinking and New Technologies to Help Enhance Employee Experience. *Deloitte*, 2023. https://www2.deloitte.com/content/dam/Deloitte/us/Documents/consulting/us-servicenow-ffex-pov.pdf

Deloitte. Deloitte's 2025 Global Human Capital Trends' Aims to Help Leaders Navigate Complex Workplace Tensions. *Deloitte*, 2025. https://www.deloitte.com/us/en/about/press-room/deloitte-report-aims-to-help-leaders-navigate-complex-workplace-tensions.html

Frank, K., & Frenette, M. Are New Technologies Changing the Nature of Work? The Evidence So Far: THE FUTURE OF SKILLS AND ADULT LEARNING ABOUT THIS STUDY, 2021.

Gansser, O. A., & Reich, C. S. A new acceptance model for artificial intelligence with extensions to UTAUT2: An empirical study in three segments of application. *Technology in Society, 65*, 2021. https://doi.org/10.1016/j.techsoc.2021.101535

García-Avilés, J. A. Diffusion of Innovation. In *The International Encyclopedia of Media Psychology* (pp. 1–8). *Wiley*, 2020. https://doi.org/10.1002/9781119011071.iemp0137

Glik, D. C., Parker, K., Muligande, G., & Hategikamana, B. Public Health Association meeting. In *International Health Section, 25*(1), 1986.

Golgeci, I., Ritala, P., Arslan, A., McKenna, B., & Ali, I. Confronting and alleviating AI resistance in the workplace: An integrative review and a process framework. *Human Resource Management Review, 35*(2), 2025. https://doi.org/10.1016/j.hrmr.2024.101075

Goodwin, M. What is an API (application programming interface)? *IBM*, 2025. https://www.ibm.com/think/topics/api

Hansen, K., & Świderska, A. Integrating open- and closed-ended questions on attitudes towards outgroups with different methods of text analysis. *Behavior Research Methods, 56*(5), 4802–4822, 2024. https://doi.org/10.3758/s13428-023-02218-x

Hattke, F., Hensel, D., & Kalucza, J. Emotional Responses to Bureaucratic Red Tape. *Public Administration Review, 80*(1), 53–63, 2020. https://doi.org/10.1111/puar.13116

Herd, P., & Moynihan, D. P. *Administrative Burden*. Published by Russell Sage Foundation, 2018. https://muse.jhu.edu/book/62771

Howard, M. C., & Rose, J. C. Refining and extending task–technology fit theory: Creation of two task–technology fit scales and empirical clarification of the construct. *Information and Management, 56*(6), 2019. https://doi.org/10.1016/j.im.2018.12.002

Hu, C., Downie, A., & Finio, M. AI Agents vs. AI Assistants. *IBM*, February 20, 2025. https://www.ibm.com/think/topics/ai-agents-vs-ai-assistants

Huynh, T. L. D., Hille, E., & Nasir, M. A. Diversification in the age of the 4th industrial revolution: The role of artificial intelligence, green bonds and cryptocurrencies. *Technological Forecasting and Social Change, 159*, 2020. https://doi.org/10.1016/j.techfore.2020.120188

Hyman, M. R., & Sierra, J. J. Open-versus close-ended survey questions. *Institute for Marketing Futurology and Philosophy*, 2016. https://www.researchgate.net/publication/282249876

Jarrahi, M. H. Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons, 61*(4), 577–586, 2018. https://doi.org/10.1016/j.bushor.2018.03.007

Jeyaraj, A. A meta-regression of task-technology fit in information systems research. *International Journal of Information Management, 65*, 2022. https://doi.org/10.1016/j.ijinfomgt.2022.102493

Lashbrooke, B. New Survey Reveals Productivity Blind Spot For Entrepreneurs. *Forbes*, November 28, 2023. https://www.forbes.com/sites/barnabylashbrooke/2023/11/28/new-survey-reveals-productivity-blind-spot-for-entrepreneurs/

Lee, J. H., & Song, C. H. Effects of trust and perceived risk on user acceptance of a new technology service. *Social Behavior and Personality, 41*(4), 587–597, 2013. https://doi.org/10.2224/sbp.2013.41.4.587

Marikyan, D., & Papagiannidis, S. *Unified Theory of Acceptance and Use of Technology*, 2023.

Moore, G. A. *Crossing The Chasm*. HarperCollins Publishers, 1991.

Muchenje, G., & Seppänen, M. Unpacking task-technology fit to explore the business value of big data analytics. *International Journal of Information Management, 69*, 2023. https://doi.org/10.1016/j.ijinfomgt.2022.102619

Na, S., Heo, S., Han, S., Shin, Y., & Roh, Y. Acceptance Model of Artificial Intelligence (AI)-Based Technologies in Construction Firms: Applying the Technology Acceptance Model (TAM) in Combination with the Technology–Organisation–Environment (TOE) Framework. *Buildings, 12*(2), 2022. https://doi.org/10.3390/buildings12020090

Nawaz, S. AI Agents vs AI Assistants. *Ampcome*, October 28, 2024. https://www.ampcome.com/post/ai-agents-vs-ai-assistants

Neumann, O., Guirguis, K., & Steiner, R. Exploring artificial intelligence adoption in public organizations: a comparative case study. *Public Management Review, 26*(1), 114–141, 2024. https://doi.org/10.1080/14719037.2022.2048685

Nugroho, M. A., & Fajar, M. A. Effects of Technology Readiness Towards Acceptance of Mandatory Web-Based Attendance System. *Procedia Computer Science, 124*, 319–328, 2017. https://doi.org/10.1016/j.procs.2017.12.161

Oranye, C. AI Assistant - Types, Advantages, & Best Platforms. *DipoleDIAMOND*, November 12, 2024. https://www.dipolediamond.com/ai-assistant-types-advantages-best-platforms/#:~:text=Virtual%20assistants%20are%20the%20most,apps%2C%20and%20social%20media%20platforms.

Orpical. Criteria for Selecting Processes Suitable for Automation: A Comprehensive Guide. *Orpical Technology Solutions*, October 22, 2024. https://orpical.com/criteria-for-automation/#Criteria_for_Identifying_Suitable_Processes_for_Automation

Parycek, P., Schmid, V., & Novak, A. S. Artificial Intelligence (AI) and Automation in Administrative Procedures: Potentials, Limitations, and Framework Conditions. *Journal of the Knowledge Economy, 15*(2), 8390–8415, 2024. https://doi.org/10.1007/s13132-023-01433-3

Pennathur, P. R., Boksa, V., Pennathur, A., Kusiak, A., & Livingston, B. A. The future of office and administrative support occupations in the era of artificial intelligence: A state of the art review and future research directions. *International Journal of Industrial Ergonomics, 104*. Elsevier B.V., 2024. https://doi.org/10.1016/j.ergon.2024.103665

Pires, P., da Costa Filho, B. A., & Mendes Junior, R. Technology Readiness Index: a study applied to students, 2023. https://aisel.aisnet.org/isla2023

Rogers, E. M. *Diffusion of Innovations*. Free Press, 1995.

Rožman, M., Oreški, D., & Tominc, P. Artificial-Intelligence-Supported Reduction of Employees' Workload to Increase the Company's Performance in Today's VUCA Environment. *Sustainability (Switzerland), 15*(6), 2023. https://doi.org/10.3390/su15065019

Schwaeke, J., Peters, A., Kanbach, D. K., Kraus, S., & Jones, P. The new normal: The status quo of AI adoption in SMEs. Journal of Small Business Management, 2024. https://doi.org/10.1080/00472778.2024.2379999

Seeber, I., Bittner, E., Briggs, R. O., de Vreede, T., de Vreede, G. J., Elkins, A., Maier, R., Merz, A. B., Oeste-Reiß, S., Randrup, N., Schwabe, G., & Söllner, M. Machines as teammates: A research agenda on AI in team collaboration. Information and Management, 57(2), 2020. https://doi.org/10.1016/j.im.2019.103174

Sengodan, A. Gartner's Technology Hype Cycle 2024: Emerging Technologies and Trends, 2024. https://www.researchgate.net/publication/385694483

Shankar Babu, N., Marda, K., Mishra, A., Bhattar, S., & Ahluwalia, A. The Impact of Artificial Intelligence in the Workplace and its Effect on the Digital Wellbeing of Employees. Journal for Studies in Management and Planning, 10(04), 024. https://www.researchgate.net/publication/379640568_The_Impact_of_Artificial_Intelligence_in_the_Workplace_and_its_Effect_on_the_Digital_Wellbeing_of_Employees

Sharma, A., & Singh, B. J. Evolution of Industrial Revolutions: A Review. International Journal of Innovative Technology and Exploring Engineering, 9(11), 66–73, 2020. https://zenodo.org/records/5853101

Spies, R., Grobbelaar, S., & Botha, A. A Scoping Review of the Application of the Task-Technology Fit Theory. Lecture Notes in Computer Science (Including Subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 12066 LNCS, 397–408, 2020. https://doi.org/10.1007/978-3-030-44999-5_33

Taherdoost, H., Mohamed, N., & Madanchian, M. Navigating Technology Adoption/Acceptance Models. Procedia Computer Science, 237, 833–840, 2024. https://doi.org/10.1016/j.procs.2024.05.172

Takyar, A. AI assistants: Types, technologies, architecture, benefits and implementations. LeewayHertz, November 2025. https://www.leewayhertz.com/ai-assistant/

Taofeek, A., Liang, W., Hamzah, F., & Mary, B. J. Overcoming Resistance to AI-Driven Change, 2024. https://www.researchgate.net/publication/389138626

Tiggelaar, M., Groeneveld, S., & George, B. Coping with administrative tasks: A cross-country analysis from a street-level perspective. Public Administration Review, 2023. https://doi.org/10.1111/puar.13745

Yin, M., Jiang, S., & Niu, X. Can AI really help? The double-edged sword effect of AI assistant on employees' innovation behavior. Computers in Human Behavior, 150, 2024. https://doi.org/10.1016/j.chb.2023.107987

Zhang, C. B., Li, T. G., Li, Y. N., Chang, Y., & Zhang, Z. P. Fostering well-being: Exploring the influence of user-AI assistant relationship types on subjective well-being. International Journal of Information Management, 79, 2024. https://doi.org/10.1016/j.ijinfomgt.2024.102822

Ziatdinov, R., Atteraya, M. S., & Nabiyev, R. The Fifth Industrial Revolution as a Transformative Step towards Society 5.0. Societies, 14(2), 2024. https://doi.org/10.3390/soc14020019

Zirar, A., Ali, S. I., & Islam, N. Worker and workplace Artificial Intelligence (AI) coexistence: Emerging themes and research agenda. Technovation, 124, 2023. https://doi.org/10.1016/j.technovation.2023.102747

Zyoud, M., Bsharat, T., & Dweikat, K. ISRG PUBLISHERS Introduction, n.d. https://doi.org/10.5281/zenodo.10939470

Biographies

Tyron Ruben Jansen (MEng) is a Process Engineer working in industry and a recent graduate of the Master of Engineering (MEng) in Engineering Management at Stellenbosch University, South Africa, which he completed cum laude in 2025. He holds a Bachelor of Engineering in Chemical Engineering from Stellenbosch University (2019). His academic and professional interests lie in applying engineering management principles in industrial and process-based environments, with a focus on improving system performance, operational efficiency, and decision-making in engineering contexts.

Michelle Smit (PhD) earned her PhD in Innovation and Technology Management from Stellenbosch University, South Africa, in 2023. She completed her BEng (Industrial Engineering) at Stellenbosch University in 2019 and is currently a lecturer in the Department of Industrial Engineering at the same institution, as well as a Candidate Engineer registered with the Engineering Council of South Africa. Her research focuses on product development, technology adoption, and customer retention within engineering and service-based industries, with particular emphasis on how innovations progress through multiple "Valleys of Death." More recently, her work explores the role of artificial intelligence in supporting product development processes and engineering customer journeys, including how multidisciplinary teams can leverage AI to improve decision-making, system performance, and customer outcomes. She has co-authored several peer-reviewed journal articles and international conference papers in the fields of engineering management and innovation.