Gordon Institute of Business Science
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Impact of Digital Transformation on Job Performance in the South African Mining Sector: The Role of Employee Engagement

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Executive Summary

This study investigated the impact of digital transformation (DT) on job performance (JP) through the mediating role of employee engagement (EE). As organisations embrace digital technologies, understanding their effect on employee outcomes, particularly JP, is vital. The research suggests DT enhances the work environment by equipping employees with advanced tools and resources, increasing engagement. Higher engagement levels improve JP, establishing EE's significant mediating role in the DT-JP relationship.

The study adopted a quantitative approach, gathering data through surveys from employees across diverse South African mining companies undergoing DT. It examined key constructs, including DT, EE, and JP, and employed Kendall's Tau correlation analysis in SPSS to explore these constructs' relationships. Its findings reveal moderate and significant DT-JP and DT-EE relationships, with a strong and significant EE-JP relationship, revealing that engaged employees are more likely to show enhanced JP.

The study further found that demographic factors such as age, educational level, job role, and work experience influence EE and JP. Employees who are older, more highly educated, in senior roles, or have greater work experience reported higher engagement levels and better JP. However, demographic factors did not significantly impact the DT construct, suggesting that the DT process applies broadly, irrespective of these factors.

Based on these findings, this study contributes to the growing body of knowledge on the role of EE in leveraging DT for improved JP outcomes. Therefore, organisations should prioritise fostering a culture of engagement while implementing DT initiatives to enhance JP. Thus, equipping employees with the right technology and promoting their engagement can improve their performance outcomes. Also, addressing their demographic differences when implementing engagement and performance strategies offers valuable insights for managers seeking to enhance technological and human resource integration.

However, this study's dependence on self-reported data may have introduced response bias, affecting its findings. Its cross-sectional design restricted its ability to establish causation. Thus, using diverse data sources, adopting a longitudinal study approach, and collecting information from multiple sectors would improve the generalisability of future research findings.

Keywords: Digital transformation (DT), employee engagement (EE), job performance (JP).

1. Chapter 1: Introduction to the Research Problem

1.1 Overview of the Research Problem

The mining industry operates within an increasingly challenging and unstable global business environment, characterised by fluctuating commodity prices, stringent environmental regulations, and dynamic economic conditions. These pressures create a combination of obstacles and opportunities, necessitating constant innovation and adaptation for long-term success (Sánchez & Hartlieb, 2020). To thrive in this complex environment, mining companies must closely monitor technological trends and invest in future-oriented innovations that enable them to adjust to rapid changes. Among these trends, digital transformation (DT) has emerged as a critical driver of innovation, offering significant potential to enhance operational efficiency, sustainability, and job performance (JP) (Lazarenko et al., 2021).

Digital technologies such as artificial intelligence (AI), automation, data analytics, and the internet of things (IoT) are reshaping mining operations, enabling organisations to streamline workflows, minimise errors, and make data-driven decisions (McKinsey & Company, 2023; Deloitte, 2024). However, the success of DT hinges not only on the adoption of these technologies but also on the active engagement of employees. Disengaged employees can resist change, limiting the effectiveness of DT initiatives, while engaged employees are more likely to embrace technological advancements, adapt to new processes, and contribute to achieving organisational goals (ami & Upadhyay, 2019).

Research highlights DT as a catalyst for innovation, integrating contemporary strategies, plans, and methods while enhancing business productivity and performance outcomes (Verhoef et al., 2021; Kraus et al., 2021). The mining sector has shown DT to influence organisational outcomes and individual EE and JP (Guzmán-Ortiz et al., 2020; Fernández-Portillo et al., 2022). By equipping employees with advanced tools and resources, DT can create a supportive work environment that fosters higher levels of engagement, enhancing JP (Barnewold & Lottermoser, 2020; Alobidyeen et al., 2022).

This chapter examines DT's drivers, barriers, and implications in the mining industry, focusing on its role in shaping business relevance and performance. Most importantly, it evaluates the relationship between DT and individual JP through the mediating effect of EE within the South African mining sector. Through this lens, the study aims to provide actionable insights into how mining companies can optimise their DT strategies to achieve sustainable performance outcomes. This chapter covers the following topics:

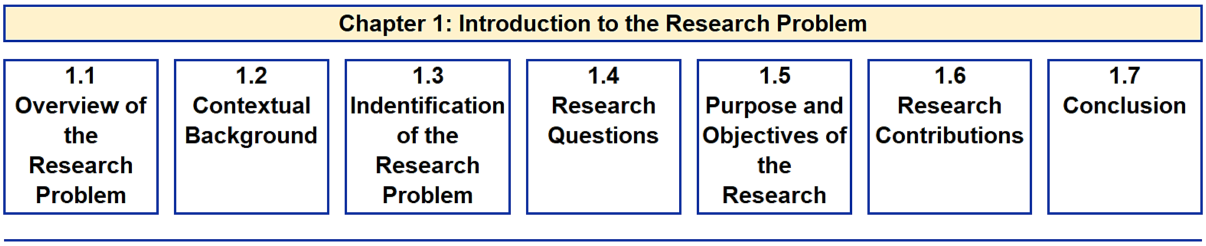

Figure 1: Chapter 1 roadmap
Source: Author's illustration

1.2 Contextual Background

1.2.1 The South African Mining Sector: Challenges and the Need for DT

The global mining industry has traditionally relied on high commodity prices, geographical advantages, equipment reliability, and robust physical assets to deliver value (McKinsey & Company, 2023a). However, the sector now faces intensifying pressures driven by decades of volatile global market conditions, declining commodity prices, ageing infrastructure, and deep orebodies with diminishing grades, collectively contributing to inefficiencies and reduced production volumes (Mareels et al., 2020; PricewaterhouseCoopers [PWC], 2024). Compounding these issues are challenges such as a shrinking skilled workforce, escalating input costs, and the increasing complexity of exploration activities in new mineral-rich locations (Sganzerla et al., 2016). The need for operational excellence, asset lifecycle optimisation, and adherence to global policy shifts further amplifies the demands placed on the industry. Stricter environmental, social, and governance (ESG) compliance targets, combined with a heightened focus on sustainability, exert additional pressure on mining employees to improve their performance and deliver enhanced value (Deloitte, 2023).

In addition to operational inefficiencies, physical risks, environmental concerns, regulatory requirements, and fluctuating commodity prices complicate the integration of digital technologies into mining operations. The sector must navigate these barriers while striving to modernise processes and meet ESG compliance requirements. Traditional approaches, such as the asset "sweating" strategy aimed at maximising the utility of existing resources, have proven insufficient to address the complex and evolving challenges of the mining sector (Eunomix, 2018). The rigid and conservative nature of traditional mining operations necessitates the adoption of digital innovations to drive meaningful change. DT emerges as a critical enabler to address these challenges by bolstering competitiveness and promoting sustainability. Advanced technologies, such as AI, automation, and real-time data analytics, can streamline workflows, reduce environmental impact, and improve decision-making by leveraging predictive insights (Buckley et al., 2020). For example, automation can lower operational costs and improve resource utilisation, while data-driven predictive maintenance reduces equipment downtime and optimises productivity (PricewaterhouseCoopers, 2024).

In response to these challenges, mining companies rapidly adapt their operating models to incorporate digital innovations. While DT holds enormous potential to enhance efficiency, safety, and sustainability, its success requires a transformative organisational culture, workforce skills, and appropriate infrastructure (Buckley et al., 2020). Without employees' engagement and active participation, DT efforts risk falling short of their transformative potential, as disengagement can hinder technology adoption and undermine organisational goals (Goswami & Upadhyay, 2019).

This research explores these dynamics, focusing on the South African mining sector, a critical contributor to the national economy and global resource supply chains (Minerals Council South Africa, 2023). By examining how DT influences JP through the mediating role of EE, this study aims to provide actionable insights for mining companies striving to optimise their DT strategies in an increasingly complex and competitive environment.

1.2.2 Current DT Implementation and JP Challenges in the SA Mining Sector

The SA mining industry is navigating a DT that presents opportunities and challenges, particularly related to the human factor. As digital technologies integrate into operational workflows, employees face increased demands to develop new skills and adapt to technology-driven environments (Sears, 2023). A significant challenge identified by (Sonnen et al. (2024) is the workforce's slow adaptation to DT initiatives, rooted in the sector's historical reliance on manual labour and conventional processes. DT goes beyond technological change; but also involves cultural shifts, requiring employees to alter established behaviours and operational practices. However, the relationship between DT and employee JP remains under-explored, making it difficult for organisations to realise the benefits of their digital investments fully (Booz Allen Hamilton, 2018).

Integrating technology into the workplace poses additional challenges. Many firms struggle to align new digital solutions with existing workflows and legacy systems, which can disrupt daily operations and hinder employee performance. Navigating incompatible systems can overwhelm employees, decreasing productivity and job satisfaction (Mining Magazine, 2023).

The entrenched organisational culture in many mining companies, which often prioritises established practices over innovation, exacerbates these challenges. This risk-averse mentality can hinder the willingness to implement DT initiatives (Boston Consulting Group, 2023). Employees may perceive the introduction of digital technologies as a threat, fostering anxiety and resistance instead of engagement. The research emphasises the importance of tailored DT implementation strategies considering employee demographics such as age, educational level, job roles and work experience to effect engagement, learning and adaptability to enhance overall JP (McKinsey & Company, 2023a).

Operating in a highly specialised and often hazardous environment, the mining workforce relies predominantly on traditional skills, which complicates the development of new digital competencies (Deloitte, 2022). Although digital technologies, such as predictive maintenance systems and real-time data analytics, offer opportunities to optimise asset utilisation and reduce downtime, their effectiveness hinges on equipping employees with the required skills and mindset (Ganeriwalla et al., 2021). Mitchell (2024) report that mining companies cite skills shortages and employee resistance as the primary barriers to their DT efforts. Addressing these human factors is crucial; otherwise, deploying digital solutions may lead to underperformance or failure to achieve desired outcomes (Accenture, 2021a).

Furthermore, the high-risk nature of mining amplifies the JP challenges linked to DT, given the close association between safety and operational efficiency with employee performance, meaning disruptions from new technologies can have significant repercussions (Heath & Christidis, 2020). Failing to engage employees in DT initiatives risks reducing productivity and increasing safety hazards. A lack of strategic alignment between DT efforts and human capital can lead to disengagement and undermine technological investments (PricewaterhouseCoopers, 2023).

Therefore, mining companies must address the human element in their DT strategies to enhance EE and JP, ensuring that technological advancements contribute to operational success rather than create additional challenges.

1.2.3 Future Potential of DT in the SA Mining Sector

The mining industry is transforming by integrating digital technologies to enhance operational efficiency, safety, and sustainability. Fluctuating commodity prices, environmental regulations, and persistent operational inefficiencies compel mining companies to explore DT to ensure competitiveness and long-term viability (Deloitte, 2023).

Digital technologies and advanced analytics offer opportunities to revolutionise operations, enabling real-time decision-making, reducing downtime, and minimising human error (Buckley et al., 2020). However, aligning DT with workforce capabilities is critical, yet this relationship remains under-explored in the existing literature.

Implementing DT initiatives provides many opportunities, such as optimising production processes, enhancing safety protocols, and reducing operational costs. AI-driven analytics and automated mining systems can significantly streamline operations from ore extraction to refining and logistics (PWC, 2023). Beyond efficiency, these digital technologies improve safety, mitigate risks and lower costs by reducing the need for human workers in hazardous environments (S&P Global, 2023). Applying DT initiatives across the mining value chain can lead to significant cost savings (Livitsanis et al., 2018; McKinsey & Company, 2023b), as shown in Figure 2.

Despite these advantages, reports show that the mining industry remains in the early stages of DT compared to other sectors, failing to fully realise its extensive benefits (Sánchez & Hartlieb, 2020). Cyber-physical systems, automation technologies, and AI are emerging as primary drivers of DT in mining, capable of revolutionising production processes by automating maintenance and decision-making (Ernst & Young, 2023). These technologies enhance productivity and operational efficiency by relieving employees of repetitive tasks, allowing them to focus on higher-value responsibilities (McKinsey & Company, 2023b). Furthermore, AI-powered predictive analytics can improve safety and efficiency by providing real-time insights into equipment performance and detecting potential hazards, significantly reducing downtime and enhancing overall productivity (Ferguson et al., 2022; Deloitte, 2023).

However, the industry's reliance on traditional, manual labour-intensive processes presents challenges to widespread DT. The human element is a critical barrier to successful DT, as transitioning to digital solutions requires a comprehensive organisational and cultural shift (Sonnen et al., 2024; Larsen et al., 2018). DT extends beyond simply deploying new technologies; it demands equipping employees with the required skills to integrate new technologies into their workflows. Accenture's survey of 151 global mining companies found that 85% of executives support internal DT initiatives, however, only 10% of employees possess the requisite human-machine integration skills (Sganzerla et al., 2016). This skills gap highlights the urgent need for specialised training programmes to bridge the gap between existing employee capabilities and the demands of a digitally transformed workplace (Nel & Treacy, 2021).

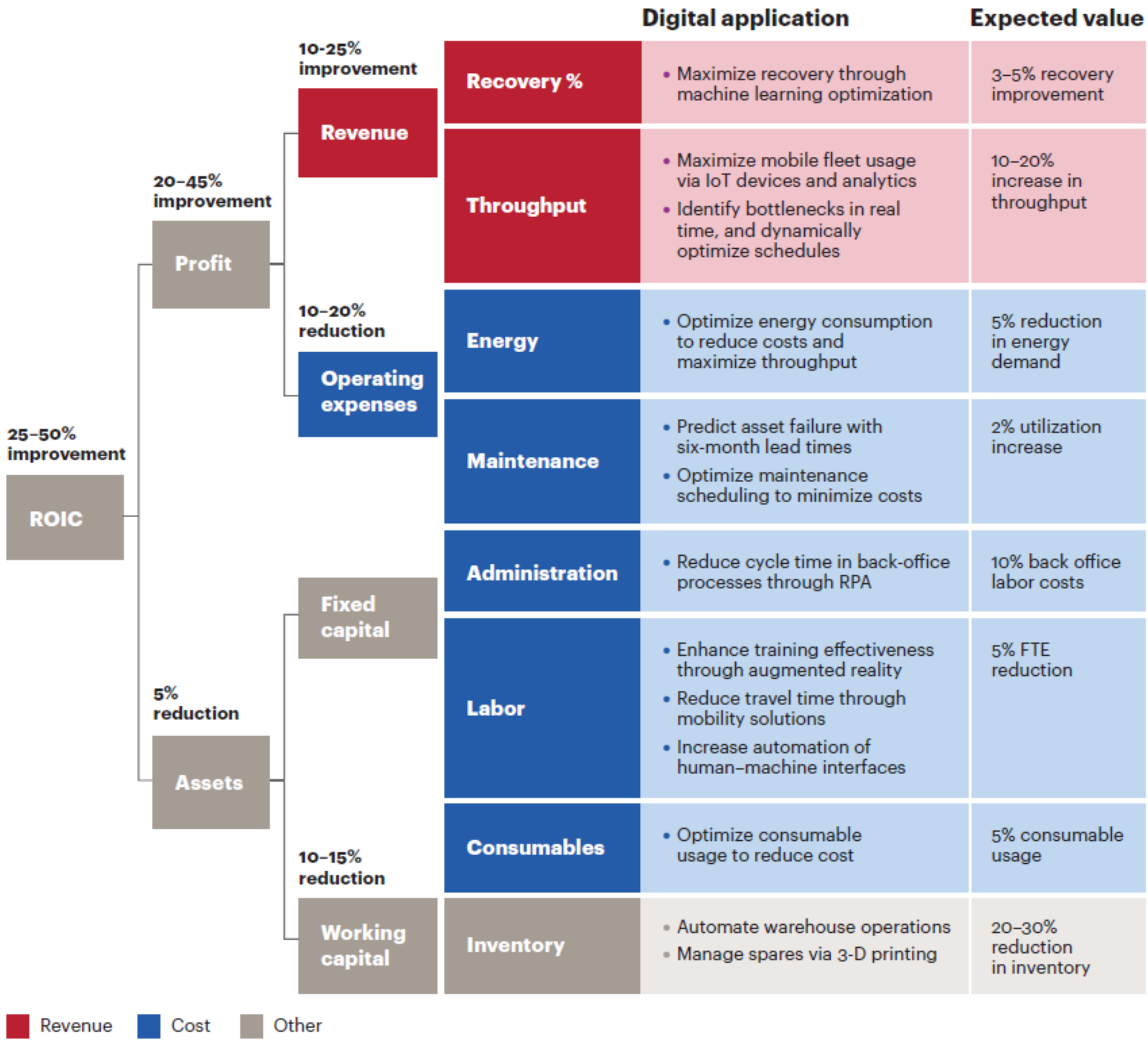

Figure 2: The potential of digital transformation improvements in the mining industry
Source: Adapted from Livitsanis et al., 2018, p.2

The Covid-19 pandemic accelerated DT across industries, including mining, as companies sought to improve operational strategies and worker safety (Nel & Treacy, 2021; Deloitte, 2023). This shift facilitated a transition from compliance-based operations to performance-driven strategies, fostering creativity, collaboration, and innovation through enhanced teamwork between human and machine operations (Nel & Treacy, 2021).

A balanced approach requires considering technological advancements and human capital for successful DT implementation in mining. While DT presents significant opportunities, it can only reach its full potential through system-wide operational visibility improvements, efficiency, and innovation. Also, workforce development is pivotal, as DT's success hinges on a company's ability to equip its workforce with the skills needed for daily operations (Nel & Treacy, 2021).

Ultimately, while DT holds promise for enhancing productivity, safety, and sustainability in mining, its successful implementation depends on addressing the human factor. Mining companies must prioritise workforce development and align organisational strategies with technological advancements to fully realise the benefits of DT (Sánchez & Hartlieb, 2020; McKinsey & Company, 2023a). By doing so, the sector can pave the way for a more efficient, competitive, and future-ready industry.

1.3 Identification of the Research Problem

The mining industry is encountering significant challenges as it strives to implement DT, with workforce dynamics emerging as a critical determinant of success. While sectors like manufacturing and finance have experienced operational improvements through automation, AI, and advanced analytics, the mining sector's DT has been slower and more complex (McKinsey & Company, 2023a). One of the main issues is the misalignment between DT initiatives and employee performance, with many mining companies neglecting to emphasise workforce readiness and JP when designing their digital strategies (Caimi & Lancry, 2018). Given the potential for DT to improve efficiency, safety, and sustainability, there is a pressing need to investigate its impact on JP within this industry.

Digital technologies offer various opportunities to enhance JP, particularly through automation and predictive analytics. Automation can reduce physical and cognitive workloads, enabling employees to focus on high-value tasks (McKinsey & Company, 2023a). Similarly, predictive analytics can enhance decision-making, operational efficiency, and safety (Deloitte, 2023). However, introducing new technologies without adequate EE or training may yield dissatisfaction or job displacement, highlighting the need for comprehensive support during DT (Caimi & Lancry, 2018).

A gap exists in the literature, as much of the current research concentrates on the technical and operational dimensions of DT rather than its impact on employee performance metrics (Accenture, 2021b). Understanding the impact of DT on the workforce is essential for industries like mining, which rely heavily on human expertise. Boston Consulting Group (2023) indicate that integrating employee training into DT strategies leads to better outcomes, highlighting the importance of workforce development. Investigating how DT influences JP through EE provides a comprehensive view of how technology and human factors shape operational results. Ignoring these elements may yield lower productivity and increased safety hazards.

EE is critical to the success of digital initiatives, as engaged employees not only perform better but also enhance safety and job satisfaction (Deloitte, 2023). Therefore, mining companies must prioritise technological advancements and human factors in their DT strategies to unlock DT's full potential. Aligning DT with EE and JP is vital for the sustainability and resilience of South Africa's mining sector in an increasingly competitive global landscape (Nel & Treacy, 2021).

1.4 Research Questions

The South African mining industry is navigating the complexities of DT, a process essential for enhancing efficiency, safety, and sustainability. However, the relationship between DT and individual employee JP remains under-explored. DT has the potential to revolutionise job functions through process streamlining and enhanced decision-making powered by real-time data (Buckley et al., 2020). Despite these advances, concerns persist about upskilling employees to integrate digital technologies into their work, emphasising the need to examine how these changes impact performance (PricewaterhouseCoopers, 2023). In a traditionally labour-intensive industry, understanding the effects of DT on individual JP is vital for assessing its broader implications on productivity and engagement (Ferguson et al., 2022).

The primary research question (PRQ) guiding this study is: **"To what extent does DT in the South African mining industry impact individual employee JP?"** This question explores how adopting technologies like automation, machine learning (ML), and advanced analytics translates into measurable performance outcomes for employees across different operational roles.

The secondary research question (SRQ) refines this focus by exploring a mediating variable: **"To what extent does EE influence the relationship between DT and individual employee JP in the South African mining industry?"** Research shows that engaged employees typically display higher productivity, motivation, and job satisfaction (Saks & Gruman, 2021). In the context of DT, EE may critically influence how effectively employees adapt to new technologies and how these technologies impact their performance (Chatterjee, Chaudhuri, et al., 2021; Breevaart & Zacher, 2019).

Investigating EE's role in mediating the effects of DT on JP is crucial for understanding the comprehensive impact of digital technologies on engagement. Scholars have argued that, without sufficient engagement, DT initiatives may not achieve their full potential, resulting in inefficiencies and suboptimal performance outcomes (Lukić-Nikolić, 2023).

1.5 Purpose and Objectives of the Research

This study investigates the impact of DT on individual JP within the South African mining industry, with particular attention to the mediating role of EE. The mining sector, traditionally characterised by manual labour and conventional operational processes, is undergoing a profound shift as it adopts digital technologies, such as automation, artificial intelligence (AI), and advanced analytics (Gregorio et al., 2020). These technological advancements are reshaping various facets of mining operations, from ore extraction to safety and maintenance procedures (PricewaterhouseCoopers, 2023). However, DT initiatives and their implementation to enhance employee JP remain under-explored in the current literature, particularly in mining, which has trailed other industries in DT (Sánchez & Hartlieb, 2020). Notwithstanding limited literature on this topic, few studies suggest that DT positively impact employee JP in other industries (Panichakarn et al., 2024; Qiao & Li, 2024).

Given the complex nature of the mining environment, where safety, efficiency, and workforce adaptability are critical concerns, this study explores how DT affects individual performance outcomes across various job roles. Scholars have emphasised that digital technologies can improve operational efficiency and safety by reducing human error and enabling data-driven decision-making (Ferguson et al., 2022). However, the success of such technologies hinges on their integration with the workforce, raising questions about how well employees can adapt to new digital technologies and whether these technologies improve or hinder JP (McKinsey & Company, 2018).

This research's secondary objective was to examine the role of EE in mediating the relationship between DT and JP. Research in organisational behaviour suggests that EE is a significant predictor of JP, with engaged employees showing higher productivity, motivation, and commitment to organistional goals (Saks & Gruman, 2021). In the mining sector, where DT requires substantial changes in operational workflows and job roles, engagement may be crucial in facilitating effective DT (Chatterjee, Rana, et al., 2021). Investigating the interplay between DT, EE, and JP through this study provides insights that can assist mining companies in designing DT strategies that optimise technological efficiency and human performance (Breevaart & Zacher, 2019).

1.6 Research Contributions

1.6.1 Practical Contributions to Industry

This study explores the relationship between DT and individual JP in the South African mining industry, while also assessing the mediating role of EE. By examining how digital technologies impact the workforce and how engagement influences their implementation, the study seeks to provide a comprehensive understanding of the interplay between DT and human capital performance. This investigation addresses a critical gap in current research, as the mining sector has traditionally been slower than other industries in digitally transforming its operations (Sánchez & Hartlieb, 2020; Vuori et al., 2019). The study findings offer practical insights for mining companies to leverage digital technologies to improve JP while ensuring the workforce remains engaged and motivated (Chatterjee, Rana, et al., 2021).

From a business perspective, the study's contributions are timely and significant. As DT reshapes the mining industry, organisations face the dual challenge of integrating advanced technologies, such as automation, AI, and data analytics, while equipping employees with the required skills to use these technologies effectively (Gregorio et al., 2020). DT initiatives promise substantial improvements in efficiency, safety, and cost reduction, but without an engaged workforce capable of leveraging these technologies, the full benefits of digitalisation may remain unrealised (PWC, 2023; Mollah et al., 2023). Understanding how EE mediates the relationship between DT and JP is crucial for mining companies aiming to maximise their return on digital investments (Guzmán-Ortiz & Martínez, 2020).

This research confirms industry insights, emphasising the importance of human factors in DT success. EE plays a pivotal role in the success of digital initiatives across industries, with higher engagement correlating with increased productivity and organisational resilience (Sonnen et al., 2024). In mining, where transitioning to digital processes requires significant changes in work practices and skills development, engagement is key to ensuring employees adopt and effectively use new technologies to enhance performance (Deloitte, 2023; Hanelt et al., 2021). By focusing on the role of EE, the study provides a deeper understanding of how mining companies can align technological advancements with human performance.

Furthermore, this research contributes to the broader discourse on workforce development in the digital age. The future of mining relies not only on technological innovation but also on the workforce's ability to adapt to new roles and responsibilities. As mining companies strive to remain competitive in an increasingly digital world, understanding the relationship between DT and JP is critical to achieving long-term success (PricewaterhouseCoopers, 2021; Young & Rogers, 2019). This study bridges the gap between academic theory and business practice, offering actionable insights that mining companies can use to design effective DT strategies that enhance operational efficiency and employee well-being.

Beyond mining, this research holds broader implications for industries similarly undergoing DT, such as manufacturing and logistics. The findings related to the interplay between DT, JP, and EE offer valuable lessons, particularly in fostering a culture of engagement to integrate digital technologies into daily operations (Qiao et al., 2024). This approach enables organisations to unlock the full potential of their digital investments, driving sustainable growth and competitive advantage in the global marketplace (McKinsey & Company, 2018, Lukić-Nikolić, 2023).

1.6.2 Academic Contributions

This study investigates the impact of DT on individual JP within the South African mining industry, focusing specifically on the mediating role of EE. This research addresses a significant gap in the current literature by examining the intersection of DT and workforce performance, a topic that remains under-explored in mining (AlNuaimi et al., 2022). Through this investigation, the study provides valuable insights into how DT influence employee JP and how engagement can be a catalyst for maximising the benefits of digital initiatives. By doing so, the research contributes theoretically and practically to the evolving discourse on DT in mining.

The academic contribution of this study is multifaceted. First, it advances the understanding of DT in the mining industry, an area where scholarly work has predominantly focused on other sectors (Vial, 2019; Vuori et al., 2019). While there is substantial literature on the operational benefits of DT (Vial, 2019; Kraus, Schiavone, et al., 2021), some studies have examined its impact on JP in other sectors such as manufacturing (Lu et al., 2019) healthcare (Kraus, Schiavone, et al., 2021), and retail (Roy et al., 2023). However, few studies have comprehensively explored the human aspects of DT, specifically its relationship with JP in the mining sector (Gruenhagen & Parker, 2020). This study addresses this gap by investigating how integrating digital technologies, such as automation, AI, and data analytics, affects individual JP in a traditionally labour-intensive industry (Hanelt et al., 2021). Understanding this relationship is critical, given that successful DT requires technological change and transformation in how employees interact with these technologies.

Second, the research contributes to the growing academic knowledge surrounding EE in the digital age. While many studies have examined EE as a predictor of JP in various industries (Saks & Gruman, 2021; Chatterjee, Chaudhuri, et al., 2021) there is limited empirical evidence that specifically considers how EE interacts with DT to influence JP outcomes in the mining sector. By examining the mediating role of EE, this study provides new insights into the mechanisms through which engagement can enhance or hinder the success of DT efforts. This contributes to the theoretical framework of EE, extending its application to contexts where DT plays a central role in operational processes (Mollah et al., 2023).

The study's findings inform academic theory and industry practice. On a theoretical level, the research contributes to the understanding of the interplay between DT, EE, and JP, offering a deep view of how these elements interact within the context of the mining industry. This adds depth to existing models of JP, which have traditionally focused on either technological factors or EE in isolation. By integrating these two perspectives, the study creates a more comprehensive framework for understanding the drivers of performance in digitally transforming industries (Hanelt et al., 2021).

Therefore, this research contributes to the scholarly literature by addressing a critical gap in the study of DT in mining, specifically its impact on individual JP and the mediating role of EE. By focusing on the South African mining sector, the study not only provides context-specific insights but also offers broader theoretical contributions that can be applied to other sectors undergoing similar transformations. These contributions have the potential to inform future research on the human aspects of DT, as well as guide industry efforts to implement digital technologies in a manner that enhances both operational efficiency and employee performance.

1.7 Introduction and Research Problem Conclusion

The mining industry faces challenges like fluctuating commodity prices, strict regulations, and declining infrastructure, necessitating continuous innovation for long-term success (Sánchez & Hartlieb, 2020). DT, powered by AI, automation, and data analytics, holds the potential to improve efficiency, sustainability, and JP (Deloitte, 2024). However, DT success depends on EE, as disengaged workers may hinder adoption and performance (Goswami & Upadhyay, 2019). Despite DT's promise, many mining companies neglect workforce readiness, leading to dissatisfaction and job displacement (Caimi & Lancry, 2018). Research on DT's impact on employee performance remains limited, focusing more on technical aspects than human factors (Accenture, 2021a). Integrating employee training into DT strategies is crucial for better outcomes. This gap in the literature emphasises the need to explore the extent to which DT affects JP through EE, as ignoring these factors could result in lower productivity and safety risks (Boston Consulting Group, 2023).

The research problem emphasises the complex relationship between digital DT, EE, and JP within the South African mining sector. While DT offers many potential benefits, including improved efficiency, safety, and sustainability, its impact on individual JP remains under-explored. The primary research question focuses on understanding the extent to which DT affects JP, while the secondary question investigates the mediating role of EE in this relationship. This inquiry is crucial, as it addresses the gap in the literature regarding the alignment between digital initiatives and workforce capabilities in an industry characterised by its traditional reliance on manual processes.

By integrating EE into the exploration of DT's impact on JP, the study provides insights that extend beyond the technical aspects of DT. The research will also examine how engaged employees are better equipped to adapt to technological advancements, ultimately contributing to enhanced performance. This focus highlights the importance of human capital in realising the full potential of digital technologies within the mining industry.

The study's academic contribution lies in its exploration of the interplay between DT, EE, and JP, adding to organisational behaviour, DT, and human resource management. Additionally, the findings offer practical insights for industry leaders seeking to implement effective digital strategies while fostering a supportive and engaged workforce.

The next chapter presents a comprehensive literature review, focusing on the key constructs of DT, EE, and JP, and exploring the theoretical foundations that underpin this study.

2. Chapter 2: Literature Review

2.1 Introduction

DT, EE, and JP are pivotal constructs shaping organisational outcomes in industries undergoing rapid technological shifts. EE serves as an underpinning theory by which this study explores the relationship between DT and its impact on engagement and JP. Despite their importance, the relationships among these three constructs remain under-explored, especially in sectors like mining that encounter distinct operational and environmental challenges (Qiao et al., 2024).

This chapter explores the DT, EE, and JP constructs in greater detail, focusing specifically on their relevance and impact on the mining industry. It further delves into the interplay between these constructs to develop its hypotheses. Through this exploration, this chapter provides a comprehensive understanding of how DT, when aligned with EE, drives improved JP, offering insights into the DT strategies in the mining sector. This chapter covers the topics shown in Figure 3 below.

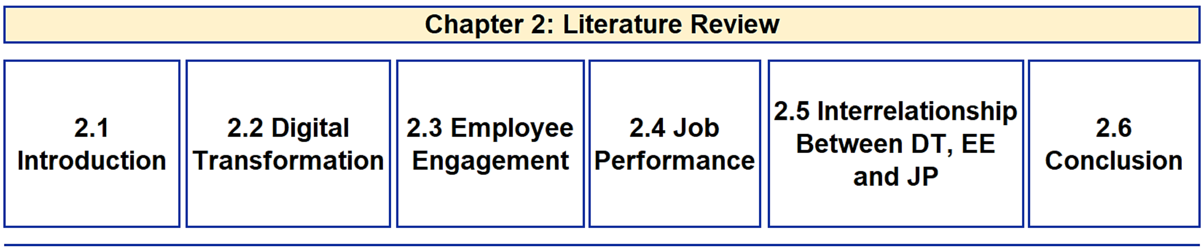

Figure 3: Chapter 2 roadmap
Source: Author's illustration

2.2 Digital Transformation

2.2.1 Definition and Scope of DT

Digital transformation (DT), also referred to as digitalisation, has gained significant attention across various sectors and regions (Saranya & Vasantha, 2023). It broadly involves the integration of information and communication technologies (ICT) into multiple facets of organisational life, affecting businesses, societies, and individuals (Vuori et al., 2019). While DT is a central topic of interest for both academics and practitioners (Hanelt et al., 2021), there is no universal agreement on its exact definition (Warner & Wäger, 2019) or scope (Wessel et al., 2021). Although several studies attempt to address this issue, most meta-analyses and systematic reviews focus on narrow aspects of DT, often coming from disciplines outside management (Vial, 2019).

The discourse on DT largely revolves around the proliferation of interconnected digital technologies, to which organisations must continuously adapt (Bharadwaj et al., 2013). Scholars such as Correani et al. (2020) and Verhoef et al. (2021) emphasise that businesses must respond to these technological shifts by realigning their operations, while Weill and Woerner (2018) note the necessity for companies to restructure their processes to remain competitive in a digital world. Traditionally, firms undergoing DT have concentrated on enhancing IT capabilities (Guzmán-Ortiz et al., 2020), but Stark (2020) suggests that this transformation also reshapes business structure, culture, and performance.

DT is more than just adopting new technologies; it involves a strategic overhaul of core business functions to improve efficiencies, decision-making, and value delivery (Verhoef et al., 2021). The process incorporates automation, AI, ML, IoT, and big data analytics to foster new business models and optimise operations (Correani et al., 2020). However, DT requires more than a technological upgrade, it demands a cultural shift within organisations, pushing them to adapt structures and processes to sustain innovation and agility (Hanelt et al., 2021). The evolving business model shapes organisations' engagement with digital technologies to remain competitive in an increasingly digital economy (Warner & Wäger, 2019).

Scholars have defined DT as a broad business transformation driven by digital technologies (Hanelt et al., 2021; Barnewold & Lottermoser, 2020). It encompasses efforts to reimagine company operations and performance (Kutnjak et al., 2019), whether through business model shifts or significant organisational change enabled by digital technologies (Vial, 2019).

2.2.2 DT in the Mining Sector

The mining industry, traditionally known for its labour-intensive operations, has been relatively slow in adopting digital technologies compared to other sectors (Sánchez & Hartlieb, 2020). However, DT has become a focal point across industries, including mining, where it involves integrating digital systems, equipment, and data to improve operational efficiency, reduce costs, and transform traditional mining processes (Barnewold & Lottermoser, 2020). The mining sector often describes DT using terms such as "mining 4.0," "smart mining," or "intelligent mining" (Henriette et al., 2015). While these terms may differ slightly, they all encapsulate the deployment of digital technologies in mining operations. As a strategic opportunity, DT initiatives align with organisational goals to enhance efficiency, reduce expenses, and revolutionise mining methods (Kutnjak et al., 2019).

For the mining industry, DT offers a substantial opportunity to enhance safety and reduce costs (Hanelt et al., 2021; Schallmo et al., 2017), improve resource allocation efficiency (Verhoef et al., 2021; Vial, 2019), improve productivity, profitability, and compliance with regulatory requirements (Young & Rogers, 2019; Olvera, 2022) and minimise risks (Young & Rogers, 2019). It opens new avenues for efficiency and collaboration throughout the value chain, providing a competitive edge across the industry (Sganzerla et al., 2016). DT impacts all aspects of mining, including drilling, haulage, communication systems, and safety monitoring (Onifade et al., 2023). The motivating factors that support these technological trends increasingly underpin the industry's direction toward adopting innovative processes (Stanway et al., 2015).

However, DT poses challenges as mining companies grapple with determining which technologies best suit their specific needs (Lazarenko et al., 2021). Though proven to improve production through automation and decentralised functions, DT in mining remains slower compared to other sectors (Young & Rogers, 2019). Smaller mining operations often underutilise digital technologies, while larger-scale enterprises implement these technologies more effectively to match their production needs (Barnewold & Lottermoser, 2020).

Key barriers to DT in mining include infrastructure limitations, risk-averse cultures (Ediriweera & Wiewiora, 2021), lack of employee upskilling, and insufficient research and development capabilities (Barnewold & Lottermoser, 2020). Resistance to change compounds these barriers at the organisational and individual levels, as suggested by Gruenhagen and Parker (2020). In the South African mining context, (Ntsoelengoe, 2019) highlighted that attitudes toward technology significantly impede widespread DT.

While mining has historically trailed other industries in DT, there is growing recognition of the potential benefits DT offers regarding safety, efficiency, and cost management (Smuts & Van der Merwe, 2022). Predictive maintenance systems powered by AI, for example, can reduce equipment downtime, while
automation enhances both the precision and speed of operations (Dayo-Olupona et al., 2023).

DT is not just about technological upgrades but requires a shift in organisational culture and structure to support continuous change and foster innovation (Hanelt et al., 2021). In mining, this means adopting technologies like AI, IoT, and big data analytics to optimise production, mitigate risks, and improve environmental sustainability (Barnewold & Lottermoser, 2020).

DT also enhances workplace safety by automating hazardous tasks, thereby reducing human involvement in dangerous environments (Young & Rogers, 2019).

Though DT offers vast opportunities, it requires a comprehensive approach that aligns digital strategies with business objectives and equips employees with the required skills to engage with these technologies (Wessel et al., 2021). Successful DT in mining hinges on a cultural shift towards agility, collaboration, and innovation (Young & Rogers, 2019) with leadership playing a pivotal role in fostering digital literacy and experimentation across the workforce.

In South Africa, digital technologies like IoT and real-time data analytics present an opportunity to tackle key challenges such as unpredictable equipment failures (Dayo-Olupona et al., 2023) high labour costs, safety concerns, and sustainability (Smuts & Van der Merwe, 2022). DT's potential to improve decision-making, reduce risks, and enhance efficiency underscores its transformative power within the mining industry.

2.2.3 Key Digital Technologies in Mining

Technology is the DT's cornerstone, acting as the primary enabler of operational improvements, innovation, and strategic growth (Hanelt et al., 2021). In the mining industry, automation, 3D printing, AI, ML, IoT and big data analytics are revolutionising traditional practices, leading to safer, more efficient, and sustainable operations (Schwarzmüller et al., 2018). These technologies allow mining companies to optimise production processes, reduce operational costs, and enhance decision-making through real-time, data-driven insights (Vial, 2019). Figure 4 shows a cluster of technologies adopted in the mining industry, with Figure 5 depicting a watered-down version of the most prevalent digital technologies.

Automation has a transformative impact on mining operations. Autonomous vehicles and machinery have reduced the need for human labour in hazardous environments, improving safety while increasing efficiency (Correani et al., 2020). Autonomous haulage systems, for example, allow trucks to operate continuously without requiring breaks, leading to higher productivity and lower labour costs (Wessel et al., 2021). Additionally, automated drilling systems have improved the precision of mining operations, reducing waste and enhancing resource recovery (Young & Rogers, 2019).

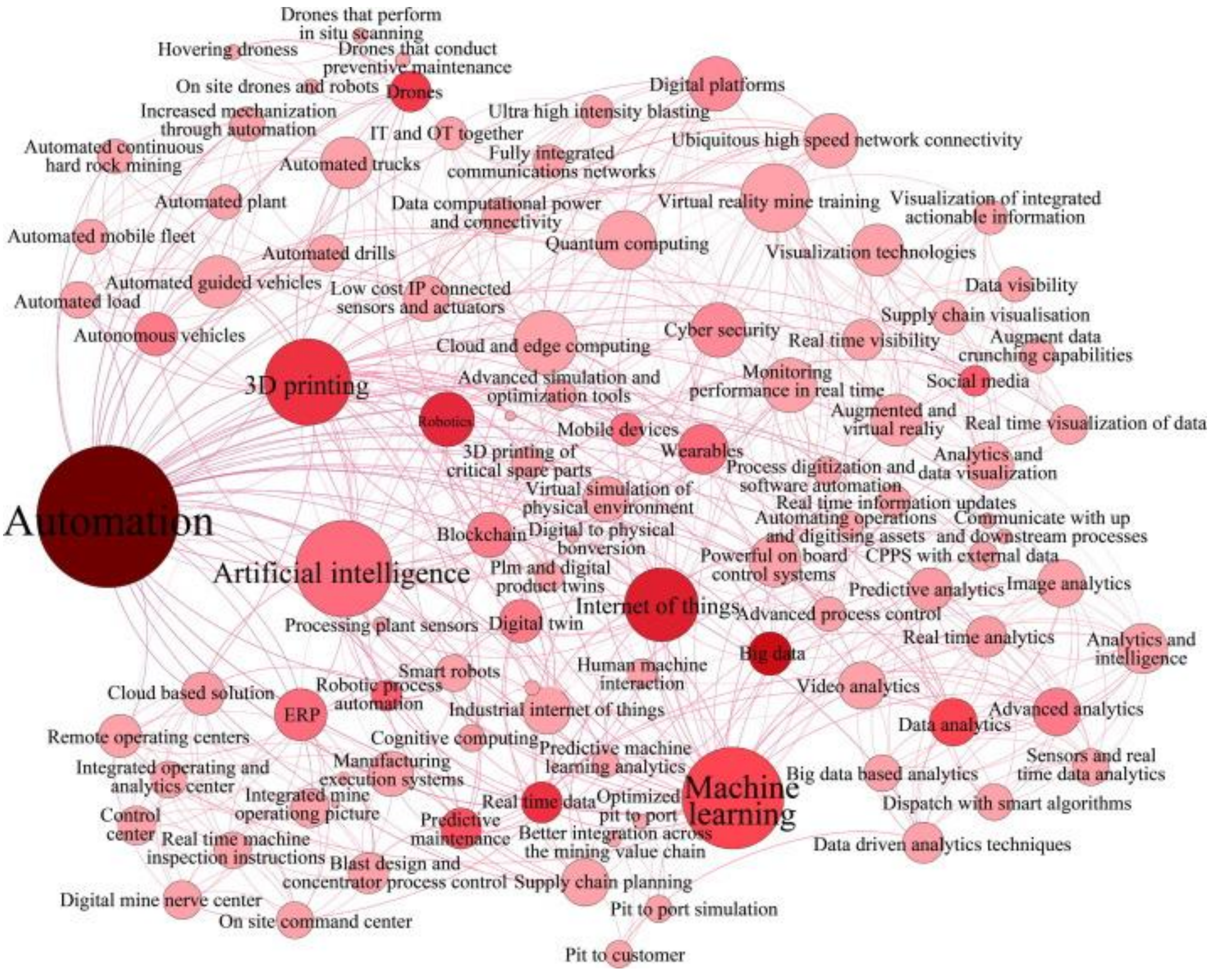

Figure 4: Digital technologies adopted in the mining industry and their associations
Source: Adapted from Barnewold & Lottermoser, 2020, p.751

3D printing, also known as additive manufacturing, has begun to play a transformative role in the mining industry by revolutionising the production of equipment parts and technologies. By enabling the on-site manufacturing of custom and complex parts, 3D printing reduces lead times and the dependency on external suppliers, leading to cost savings and increased operational efficiency (Ngo et al., 2018). This technology also enhances sustainability by minimising waste, as it produces parts with precision and consumes fewer resources. Furthermore, 3D printing allows for rapid prototyping, which accelerates the innovation process in designing new mining technologies and machinery components (Chen et al., 2022).

AI plays a critical role by analysing vast amounts of data collected from sensors and other sources, identifying patterns, and predicting outcomes that would otherwise be difficult for humans to detect (Schallmo et al., 2017). AI and ML are essential for predictive maintenance, where these technologies use historical and real-time data to predict equipment failures before they occur (Warner & Wäger, 2019). By minimising unplanned downtime, AI improves productivity and reduces costs associated with repairs and equipment replacement (Smuts & Van der Merwe, 2022). Similarly, ML algorithms analyse geological data to identify the most promising areas for exploration, reducing the time and cost of finding new mineral deposits (Vuori et al., 2019).

ML is emerging as a key enabler of predictive maintenance, resource exploration, and operational optimisation in the mining industry. By analysing vast datasets, ML algorithms can identify patterns and trends that are difficult to detect manually, enabling more accurate predictions of equipment failures and resource availability (J. Duque et al., 2024; Jooshaki et al., 2021). ML also optimises the extraction process by analysing real-time data and adjusting operations to improve efficiency and reduce energy consumption (Jung & Choi, 2021). The application of ML in exploration activities has significantly enhanced mineral discovery rates, reducing the time and cost involved in finding new deposits (Kwayisi et al., 2024).

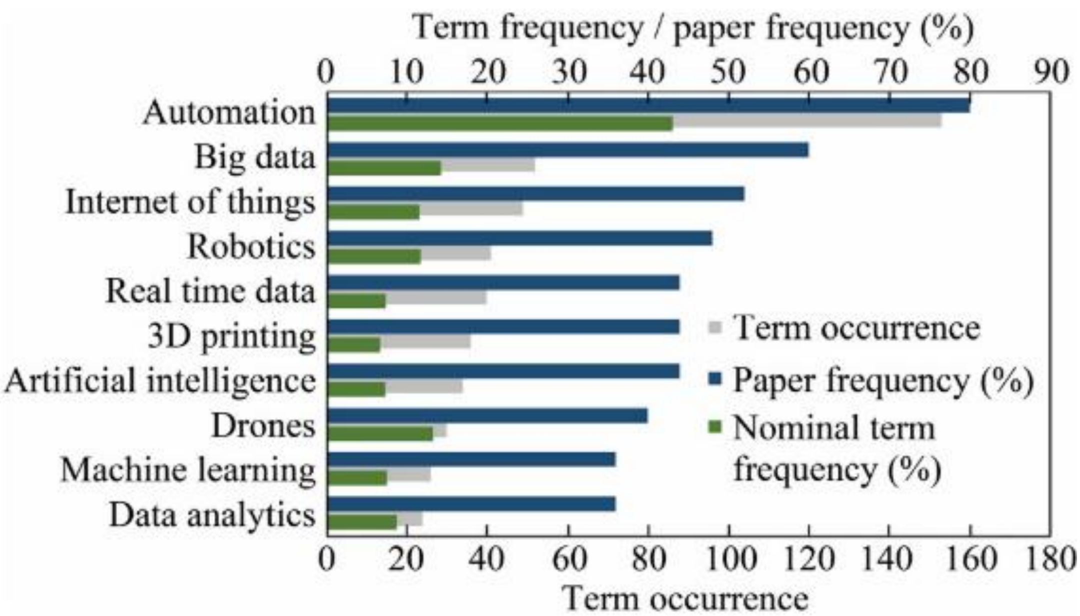

Figure 5: The most prevalent technologies in the mining industry
Source: Adapted from Barnewold & Lottermoser, 2020, p.750

IoT plays a pivotal role in DT by enabling real-time monitoring of equipment performance and environmental conditions (Barnewold & Lottermoser, 2020). IoT sensors collect continuous data on equipment functionality, geological conditions, and safety risks, allowing mining companies to make more informed decisions and respond quickly to potential hazards (Schwarzmüller et al., 2018). For instance, IoT-enabled sensors can detect gas leaks or equipment malfunctions, enabling quick responses that prevent accidents and reduce downtime (Verhoef et al., 2021). This technology allows mining operations to detect risks, such as equipment malfunctions or safety violations in real time, reducing downtime and operational delays (Zohra et al., 2022).

Big data analytics further enhance the capabilities of mining companies by providing deeper insights into operational efficiency and resource utilisation. By analysing data from multiple sources, including geological surveys, equipment sensors, and production reports, big data analytics identifies opportunities for process optimisation, cost reduction, and productivity improvements (Ye et al., 2024).

2.2.4 Factors Influencing DT in Mining

The mining sector, traditionally reliant on labour-intensive processes, is undergoing a paradigm shift fuelled by digital integration. DT in this sector promises improved operational efficiencies, enhanced safety, and increased environmental sustainability (Correani et al., 2020). However, several factors shape the pace and success of transitioning to a digitalised mining environment. These factors include technological advancements (Lasi et al., 2014), workforce readiness (Bresciani et al., 2021; Zhang et al., 2018), leadership support (Müller et al., 2024), regulatory frameworks (Zhou, 2024), and financial considerations (Onifade et al., 2023).

2.2.4.1 Operational Efficiency

The need to improve maintenance and optimise resource extraction is driven by the availability and maturity of emerging technologies to predict equipment failures, reduce downtime and increase operational efficiency (Sánchez & Hartlieb, 2020). Similarly, IoT allows for real-time monitoring of geological and environmental conditions, enhancing safety and decision-making (Schwarzmüller et al., 2018). The need for efficient data collection, storage, and analysis capabilities enables real-time decision-making and process optimisation, making data management a key enabler of DT (Vial, 2019). Furthermore, the need to optimise logistics and safety has led to the adoption of autonomous vehicles and drones, which have transformed transportation and surveying tasks, reducing human involvement in hazardous activities and improving accuracy (Niu et al., 2024). Despite these advancements, the successful implementation of these technologies depends on the organisation's digital infrastructure, including high-speed data networks and cloud-based platforms, which facilitate the seamless exchange of information and remote monitoring capabilities (Schallmo et al., 2017).

2.2.4.2 Workforce Readiness

Workforce readiness is a critical factor influencing the DT of the mining sector. Implementing digital technologies requires a workforce with the required skills to operate and manage advanced systems (AlNuaimi et al., 2022). However, the traditional mining workforce is accustomed to manual labour and mechanical operations, creating a significant skills gap (Trenerry et al., 2021). This skills mismatch often leads to resistance to DT, as workers fear job displacement or struggle to adapt to the new digital landscape (Hanelt et al., 2021).

2.2.4.3 Leadership and Culture

Transformational leadership supports DT and aligns it with business goals (Hanelt et al., 2021) by promoting a clear strategic vision, motivating, and empowering employees (Breevaart & Zacher, 2019), fostering a supportive organisational culture that values continuous learning, experimentation, and adaptability (Macey & Schneider, 2008), innovation and collaboration is critical to DT success (Wessel et al., 2021). Furthermore, organisations cultivating a culture of openness and inclusivity are better positioned to overcome DT implementation challenges, particularly in the mining sector, where the workforce may be resistant to change (Trenerry et al., 2021).

2.2.4.4 Regulatory Factors

Mining operations are subject to strict environmental regulations, safety standards, and labour laws, all of which significantly support the industry's DT (Smuts & Van der Merwe, 2022; Dayo-Olupona et al., 2023). Digital technologies such as IoT sensors and data analytics platforms assist mining companies with monitoring air quality and water usage, ensuring that operations comply with environmental standards and reduce their ecological footprint (Wang et al., 2022).

2.2.4.5 Market and Economic Factors

Fluctuating commodity prices and the need to reduce operational costs push mining companies to adopt DT to remain competitive and sustainable. Financial considerations significantly shape the industry's DT, as it often requires substantial upfront investments in infrastructure, training, and equipment (Correani et al., 2020). Smaller mining companies, in particular, may face financial constraints that limit their ability to embrace DT fully, especially if the return on investment (ROI) is uncertain (Smuts & Van der Merwe, 2022). Furthermore, financial incentives, such as government subsidies and tax breaks for DT, alleviate some of the industry's financial pressures (Schallmo et al., 2017)

2.2.5 Barriers to Successful DT in Mining

Despite DT's potential, the mining industry faces significant barriers to its implementation, spanning from the skills gap between the current workforce and the digital competencies required to manage advanced technologies. Mining employees, traditionally trained in manual labour and mechanical operations, may struggle to adapt to the digital technologies and systems that are becoming integral to modern mining practices (Trenerry et al., 2021). This skills mismatch creates resistance to DT, as employees fear job displacement or lack the expertise needed to operate new technologies (Hanelt et al., 2021).

In addition to workforce resistance, financial constraints present a significant obstacle to DT's successful implementation. The high upfront costs associated with purchasing and integrating digital technologies can be prohibitive, particularly for smaller mining companies with limited capital (Sánchez & Hartlieb, 2020). Legacy systems and outdated infrastructure further complicate DT efforts, as companies must invest in upgrading existing systems to support advanced technologies (Smuts & Van der Merwe, 2022).

Long lead times required to fully implement DT initiatives add to workforce resistance and financial barriers. Many mining companies are hesitant to commit to such investments due to the uncertainty surrounding return on investment (ROI) and the potential for disruptions to traditional workflows (Gruenhagen & Parker, 2020). The extended time required for DT initiatives to generate measurable financial benefits can lead to scepticism within the industry regarding their overall value (Ye et al., 2024).

Ineffective DT strategies can have far-reaching consequences for mining companies. Failure to address workforce resistance, skills gaps, and financial challenges can cause incomplete or unsuccessful DT initiatives, leading to wasted resources and missed opportunities for operational improvement (Olvera, 2022). Furthermore, companies that fail to keep pace with DT risk falling behind competitors that have successfully implemented advanced technologies (Noesgaard et al., 2022). To mitigate these risks, mining companies must develop comprehensive DT strategies that address both the technical and human dimensions of transformation, ensuring that employees are engaged, skilled, and supported throughout the process (Wessel et al., 2021).

2.3 Employee Engagement (EE)

2.3.1 Defining EE

Engagement in the workplace refers to the psychological, emotional, and behavioural commitment that employees exhibit towards their jobs, significantly impacting their performance, productivity, and loyalty to the organisation. This multifaceted concept encompasses enthusiasm, motivation, dedication, and active participation in job-related tasks (Bailey et al., 2017b). Research shows that engaged employees display heightened levels of energy and commitment, which can drive improvements in JP, innovation, and overall organisational success (Shuck et al., 2017).

Kahn's (1990) model anchors the engagement theory, which suggests that engagement emerges when employees perceive psychological meaningfulness, safety, and availability in their work. Specifically, meaningfulness arises from finding value in one's contributions. Safety refers to the assurance of engaging without fear of negative repercussions, and availability pertains to the emotional, physical, and cognitive presence of employees (Kahn, 1990). Modern theories have expanded on Kahn's work, incorporating elements such as job resources, leadership, and organisational culture as essential factors influencing engagement (Albrecht et al., 2015).

EE is a crucial driver of organisational effectiveness. Companies that prioritise engagement typically experience enhancements in performance, retention, innovation, and customer satisfaction (Correani et al., 2020). Engaged employees often take ownership of their roles, actively contributing towards the achievement of organisational goals, which not only boosts productivity but also job satisfaction, both of which can significantly influence the financial health of the organisation (Bailey et al., 2017).

In industries undergoing rapid transformation, such as mining, EE is particularly vital. As DT introduces new technologies and processes, engaged employees are more likely to adapt effectively to these changes, thereby supporting the success of such initiatives (Alobidyeen et al., 2022). Furthermore, in high-risk sectors like mining, engagement is essential for ensuring safety, precision, and collaboration, resulting in reduced accidents and improved operational performance (Dayo-Olupona et al., 2023).

Finally, organisational culture plays a pivotal role in nurturing EE. A culture that fosters trust, open communication, and collaboration enhances employees' sense of belonging and overall engagement (Hooi & Chan, 2023). This holistic approach to engagement benefits the individual and significantly enhances the organisational landscape, paving the way for sustained success.

2.3.2 Frameworks for Understanding EE

The study of EE has evolved considerably since Kahn's (1990) seminal model, which laid the foundation for understanding the psychological conditions necessary for engagement at work. Several models have since built upon Kahn's work, integrating additional dimensions and contextualising engagement in various organisational settings. The following section reviews the evolution of key EE frameworks, from Kahn's foundational model to contemporary approaches.

2.3.2.1 Kahn's Engagement Model

Kahn's (1990) model of "psychological conditions of personal engagement and disengagement at work" provides a foundational framework for understanding EE. According to Kahn, engagement occurs when employees feel psychologically safe and available, and find meaning in their work, allowing them to invest their cognitive, emotional, and physical energies. Psychological safety enables employees to express thoughts without fear, while availability reflects the personal resources they can contribute to their roles, and meaningfulness enhances motivation (Eldor & Vigoda-Gadot, 2017; Soane et al., 2013).

Recent studies have broadened Kahn's framework to encompass emotional intelligence, leadership styles, and DT, highlighting the wider organisational and environmental influences at play (Jiang & Men, 2017). Transformational leadership is particularly significant in enhancing psychological safety and meaningfulness, especially in organisations undergoing rapid technological change (Breevaart & Zacher, 2019). In technology-driven contexts, disengagement may arise when employees feel unprepared for new digital technologies (Correani et al., 2020). However, employees' digital skills and support systems can positively influence psychological safety and availability (Bakker, A. B., & Demerouti, 2017). Positive psychology underscores strengths, resilience, and well-being as key drivers of engagement (Bakker & Albrecht, 2018).

Furthermore, the rise of remote and hybrid work has complicated the maintenance of psychological safety, necessitating virtual technologies and effective communication strategies to foster engagement in these settings (Lukić-Nikolić, 2023). The job demands-resources (JD-R) model further complements Kahn's concept of availability by illustrating how balancing job demands and resources sustains engagement over time (Bakker & Demerouti, 2017). Thus, Kahn's model has evolved to include contemporary organisational realities, integrating leadership, emotional intelligence, technology, job resources, and the changing nature of work, making it increasingly relevant in today's complex organisational landscape.

2.3.2.2 The Job Demands-Resources (JD-R) Model

The job demands-resources (JD-R) model, developed by Demerouti et al. (2001), is a widely influential framework for understanding EE, focusing on the balance between job demands (e.g., workload, time pressure) and job resources (e.g., autonomy, support, development opportunities). Job resources play a key motivational role by enhancing employees' energy and focus, which fosters engagement, productivity, and resilience in managing demands (Bakker & Demerouti, 2007). This model with a schematic representation in Figure 6 model is versatile, applying across industries and various job contexts.

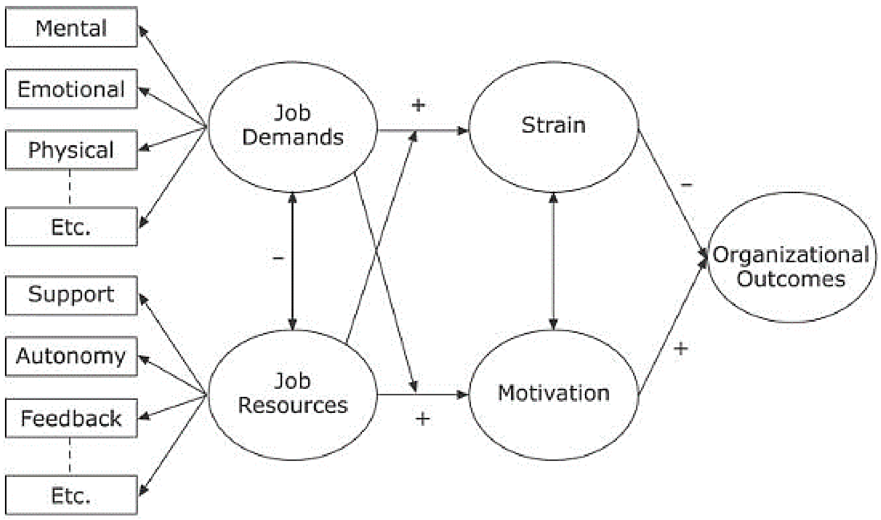

Figure 6: Job-demand resource model
Source: Adapted from Bakker & Demerouti, 2007, p. 313

Recent developments have expanded the JD-R model to emphasise that job resources not only mitigate the impact of job demands but also foster a positive work environment that enhances engagement (Bakker & Demerouti, 2017). The model now highlights the dual processes of job demands leading to strain and disengagement if unmanaged, while job resources enhance motivation, driving engagement, and positive organisational outcomes (Lesener et al., 2019). Additionally, the inclusion of personal resources, such as self-efficacy, optimism, and resilience, has emerged as a significant factor in moderating the relationship between job demands and engagement. Employees with higher personal resources are more adept at leveraging job resources and maintaining engagement, even under high job demands (Bakker & van Wingerden, 2021).

Adaptation of the JD-R model to modern work environments includes DT and remote work. Digital technologies can serve as job resources when they enhance autonomy and support but may increase job demands if they overwhelm employees (Ye et al., 2024). Additionally, engaging leadership is a critical job resource, as leaders can foster engagement by providing feedback and support (Breevaart & Zacher, 2019).

Overall, the JD-R model continues to offer insights into how organisations can balance demands and resources to drive EE, particularly in the evolving, technology-driven workplace.

2.3.2.3 Schaufeli's Worker Engagement Model

Wilmar Schaufeli's work, alongside Arnold Bakker, significantly advanced the understanding of EE by introducing a model that frames engagement as a positive, fulfilling, work-related state characterised by vigour, dedication, and absorption (Schaufeli & Bakker, 2004). Unlike Kahn's (1990) psychological conditions model, Schaufeli's approach focuses on the affective and motivational aspects of engagement. Vigour refers to high energy and resilience at work, dedication reflects strong involvement and a sense of purpose, and absorption describes being deeply engrossed in tasks (Carmona-Halty et al., 2019; Eldor & Vigoda-Gadot, 2017).

Industries have widely adopted Schaufeli's model. It remains relevant in modern workplaces, especially with the rise of DT and remote work. Studies show that vigour, dedication, and absorption help employees adapt to technological changes, maintaining high engagement levels in virtual and hybrid environments (Breevaart & Zacher, 2019; Lukić-Nikolić, 2023). The model is particularly effective in high-stress sectors such as healthcare and education, where emotional and mental resilience are critical (Salanova, 2023). Schaufeli's dimensions have been linked to increased employee retention, reduced turnover, and heightened organisational commitment, making it a robust framework for assessing engagement (Bakker & Albrecht, 2018).

2.3.2.4 The Emotional Engagement Model

Macey and Schneider's (2008) extension of Kahn's model focused on EE's emotional and affective components. While Kahn (1990) emphasised psychological conditions, Macey and Schneider argued that emotional engagement is critical in driving commitment and performance. Emotionally engaged employees demonstrate higher enthusiasm, dedication, and a willingness to exceed job expectations. This emotional connection enhances discretionary effort, motivating employees to invest more energy and creativity due to their attachment to the organisation (Macey & Schneider, 2008). Figure 7 depicts the emotional engagement model framework.

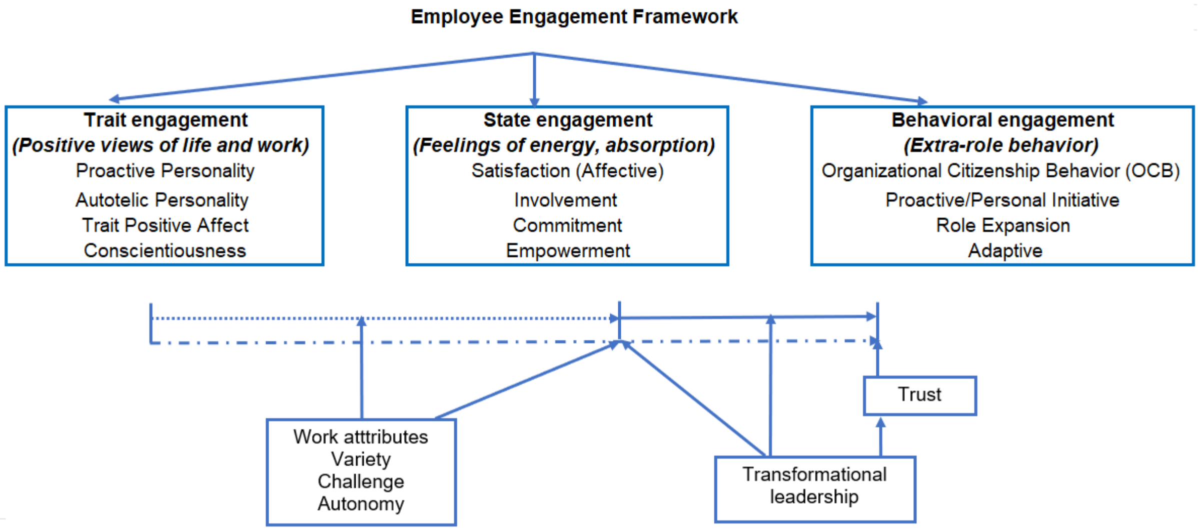

Figure 7: Emotional engagement framework
Source: Author's illustration based on Macey & Schneider, (2008)

Recent studies support this model, showing that emotional engagement fosters individual performance and organisational outcomes, such as retention, innovation, and adaptability (Jiang & Men, 2017). Emotional engagement helps create a positive workplace culture where employees feel valued, reducing turnover intentions (Bakker & Albrecht, 2018). Emotional intelligence is crucial, as emotionally intelligent employees better handle workplace stress and build stronger relationships, contributing to sustained engagement (Schlaegel et al., 2022).

As remote work rises, maintaining emotional engagement has become challenging. Research suggests strategies such as regular check-ins, virtual team-building, and recognition programs to maintain emotional connections in virtual settings (Lukić-Nikolić, 2023). Leadership styles, such as transformational leadership, significantly enhance emotional engagement by fostering open communication and aligning employees with organisational goals (Breevaart & Zacher, 2019; Bakker & Demerouti, 2017).

Additionally, psychological empowerment, where employees feel control over their work and see their contributions as meaningful, further strengthens emotional engagement and performance (Eldor & Vigoda-Gadot, 2017). Organisational support through flexible work arrangements and recognition programs reinforces employees' commitment, enhancing overall engagement and performance (Saks, 2019).

2.3.3 Factors Influencing EE

Several factors drive EE, including job satisfaction, organisational culture, leadership, and job resources. Job satisfaction enhances emotional engagement, while a positive organisational culture supports psychological alignment with company values (Trenerry et al., 2021). Leadership inspires behavioural engagement through clear communication and support. Job resources like autonomy and growth opportunities further boost engagement by enabling efficient task performance (Bailey et al., 2017a). Together, these factors shape employees' emotional, psychological, and behavioural involvement in their work

2.3.3.1 Job Satisfaction

Job satisfaction remains a critical determinant of EE. Employees satisfied with their work conditions, compensation, and career opportunities are more likely to be engaged. Satisfaction with intrinsic factors, such as meaningful work and autonomy also plays a significant role in fostering engagement. The degree to which employees find their work fulfilling correlates directly with their motivation and commitment to organisational objectives (Saks, 2019; Perera et al., 2018).

2.3.3.2 Organisational Culture

Organisational culture significantly shapes EE. Cultures rooted in trust, open communication, and collaboration promote a sense of belonging and commitment, enhancing engagement levels. In such environments, employees feel valued, which boosts motivation and performance. Conversely, bureaucratic or toxic cultures often result in disengagement, where employees feel isolated from leadership and organisational goals, leading to reduced job satisfaction and productivity (Bakker et al., 2020).

2.3.3.3 Leadership

Leadership style is another critical driver of engagement. Transformational leadership, characterised by inspirational vision, support, and encouragement, positively influences engagement levels (Breevaart & Zacher, 2019; Trenerry et al., 2021). Leaders who actively involve employees in decision-making, provide feedback, and recognise their contributions foster higher levels of engagement (Bakker & Albrecht, 2018). Employees feel motivated to align their personal goals with organisational objectives, thereby increasing their emotional investment in the company (Shuck et al., 2017).

2.3.3.4 Job Resources

The availability of job resources such as training, development opportunities, and autonomy is essential for fostering engagement. According to the JD-R model, job resources serve as motivators that promote engagement, as they help employees meet job demands while achieving personal growth (Bakker & Demerouti, 2017). Employees who feel equipped with the technologies, knowledge, and support necessary to perform their tasks are more likely to be engaged and committed to their work.

2.3.4 EE in Technology-Driven Environments

In technology-driven work environments, particularly those undergoing DT, EE becomes even more critical. The successful implementation of DT relies heavily on EE. Engaged employees are more likely to adapt to new technologies and contribute positively to the success of digital initiatives, leading to better organisational outcomes (Bakker & Albrecht, 2018). Conversely, disengaged employees may resist technological change, resulting in decreased productivity, increased frustration, and higher levels of job dissatisfaction (Correani et al., 2020; Smuts & Van der Merwe, 2022; Schallmo et al., 2017). By fostering engagement, organisations can ensure that employees remain motivated and adaptable in the face of technological advancements (Macey & Schneider, 2008; Alobidyeen et al., 2022).

EE also plays a role in mitigating the challenges associated with DT. Providing employees with the necessary resources, training, and support to navigate new technologies is essential for maintaining high levels of engagement (Dayo-Olupona et al., 2023; Bakker & Demerouti, 2017). When employees feel confident in their ability to use digital technologies, they are more likely to remain engaged and motivated, leading to enhanced JP and overall organisational success (Picazo Rodríguez et al., 2024).

2.4 Job performance (JP)

2.4.1 Importance of JP

Individual JP is a critical construct in organisational psychology and HR management due to its direct link to organisational success. High JP enhances productivity, innovation, and competitive advantage, while poor performance leads to inefficiencies and increased costs (Carter et al., 2018; Bakker & Demerouti, 2017). This is particularly significant in industries like mining, where optimising JP is essential for meeting operational goals and sustaining growth. With the rise of DT, the focus on human capital has increased as organisations seek to leverage technological advancements alongside employee performance (Vo-Thanh et al., 2021).

Globalisation and technological disruptions have heightened the importance of adaptability, EE, and digital skills in enhancing performance (Breevaart & Zacher, 2019). Organisations that invest in continuous employee development are more likely to enjoy better outcomes, including profitability and market share. Understanding the drivers of JP, particularly task and contextual performance, is crucial for maintaining competitive advantages in volatile markets (Carter et al., 2018).

High performers also experience greater job satisfaction and are less likely to leave, contributing to a culture of excellence that drives innovation and performance standards across the workforce (Buil et al., 2019). In an era of DT and remote work, fostering high performance remains vital for long-term success.

2.4.2 Defining JP

JP is a multifaceted concept that encompasses the effectiveness, quality, and efficiency with which individuals execute their work roles (Carter et al., 2018). The traditional definition of JP refers to an individual's capacity to perform their assigned duties and responsibilities. However, modern definitions have expanded to include broader behavioural and organisational aspects, such as the ability to collaborate with colleagues, adapt to changes, and contribute to organisational goals beyond one's direct tasks (Buil et al., 2019).

Carter et al. (2018) define JP as a multidimensional construct that consists of both task performance which is the completion of core job responsibilities, and contextual performance, which involves activities that contribute to the broader organisational environment, such as teamwork and organisational citizenship behaviours (OCB). This expanded understanding acknowledges that employees' contributions go beyond their direct tasks, recognising that interpersonal relationships and environmental factors significantly influence overall performance. Research highlights that social and contextual elements, such as teamwork, communication, and the organisational climate, play a crucial role in enhancing job outcomes and EE, ultimately driving higher performance (Breevaart & Zacher, 2019). These factors shape how effectively employees apply their skills and collaborate to achieve organisational objectives.

Defining JP in today's rapidly changing work environments also involves accounting for adaptive performance, or the ability to adjust to new work conditions and expectations brought about by technological change, globalisation, and evolving organisational structures (Buil et al., 2019). This adaptability has become increasingly relevant in industries experiencing significant technological disruptions, such as mining, where employees must regularly acquire new skills and navigate complex digital technologies to perform their jobs effectively (Bakker & Demerouti, 2017).

2.4.2.1 Task Performance

Task performance is the execution of specific duties and responsibilities outlined in an individual's job description. Scholars regard task performance as a key indicator of an employee's contribution to organisational productivity, particularly in sectors like manufacturing and mining, where it aligns with outcomes such as production rates, error reduction, and safety compliance (Carter et al., 2018; G. Research highlights its importance in driving operational efficiency and competitive advantage (Bakker & Demerouti, 2017). In these industries, effective task performance ensures that employees meet organisational goals while maintaining high standards of accuracy and safety (Buil et al., 2019).

In recent years, the increasing use of automation and AI has also influenced task performance in many industries, including mining. Digital technologies can enhance employees' task performance by providing real-time data, automating routine tasks, and improving decision-making processes (Breevaart & Zacher, 2019). However, integrating such technologies requires employees to adapt to new working methods, highlighting the need for continuous skill development to maintain high task performance. Studies reveal that well-supported employee skill development boosts task proficiency and job satisfaction (Buil et al., 2019).
Additionally, job resources such as training, leadership, and access to necessary technologies and technology influence task performance. When these resources are

available, employees are more likely to perform their tasks effectively and efficiently, boosting individual and organisational outcomes (Carter et al., 2018).

2.4.2.2 Contextual Performance

Contextual performance encompasses activities that go beyond formal job duties but are essential for maintaining a productive organisational environment. This includes organisational citizenship behaviours (OCBs), such as helping colleagues, volunteering for extra tasks, and upholding the organisation's values and standards (Buil et al., 2019). While task performance focuses on completing specific responsibilities, contextual performance reflects an employee's broader contribution to the organisational culture and climate. It also plays a critical role in promoting teamwork, cohesion, and the smooth functioning of work processes (Gordon et al., 2018).

Contextual performance has gained increasing attention as successful operations depend not only on employees fulfilling their technical responsibilities but also on their willingness to engage in behaviours that support the collective well-being of the organisation. In industries such as mining, where collaboration is often necessary for complex projects, contextual performance is crucial for ensuring safety, efficiency, and innovation (Vo-Thanh et al., 2020).

Furthermore, contextual performance aligns with higher levels of EE and job satisfaction. Employees engaged in OCBs report more positive relationships with colleagues, greater job fulfilment, and a stronger sense of loyalty to their organisation (Bakker & Demerouti, 2017). Regarding DT, contextual performance becomes even more significant, as employees who actively contribute to knowledge sharing and problem-solving are essential for integrating new technologies and adapting to changes (Breevaart & Zacher, 2019).

2.4.3 JP Context the Mining Industry

The mining industry presents unique challenges and opportunities for understanding JP. Given the sector's reliance on manual labour and technological advancements, evaluating individual performance combines task efficiency, safety compliance, and the ability to adapt to new technologies (Onifade et al., 2023). Integrating digital technologies such as automation, AI, and big data analytics has transformed traditional mining roles, making it essential for employees to balance technical skills with adaptability and teamwork (Hanelt et al., 2021).

Because of extreme safety concerns, the mining industry aligns individual JP with the employee's ability to adhere to safety protocols and contribute to a safety culture within their teams. In this context, contextual performance, such as supporting colleagues and reporting hazards, becomes as important as task performance in maintaining safe and productive operations (Breevaart & Zacher, 2019).

Recent studies show that DT in mining has reshaped JP metrics, emphasising employees' ability to operate complex machinery and use data-driven technologies for decision-making (Correani et al., 2020). This shift requires continuous training and development, including fostering an organisational culture that supports learning and collaboration. Employees who are engaged and feel supported in their development are more likely to adapt to new technologies and maintain high performance in an evolving industry (Buil et al., 2019).

Furthermore, the mining industry aligns JP with employee contributions to sustainability initiatives and compliance with environmental regulations, because of increasing environmental sustainability requirements. Employees are now expected to integrate sustainable practices into their daily tasks, highlighting the need for a holistic approach to performance management in the mining industry (Onifade et al., 2023).

2.5 Interrelationship Between DT, EE and JP

2.5.1 DT's Impact on JP

DT has emerged as a critical factor in reshaping modern workplaces, altering how employees approach and perform their roles. Organisations incorporate advanced digital technologies to optimise operations, improve decision-making, and foster greater innovation, all of which positively influence employee productivity and performance (Correani et al., 2020). Thus, EE plays a vital role in connecting DT to improved JP, as engaged employees are more likely to embrace technological changes, adapt to new systems, and boost their performance (Breevaart & Zacher, 2019). This study's hypothesis 1 suggests that **"DT has a significant positive association with employee JP".** To understand to what extent this hypothesis holds, it is important to explore how DT influences JP and the factors contributing to its success.

One of the primary ways DT drives JP is through automation. By automating routine and repetitive tasks, digital technologies free up employees' time, allowing them to focus on more complex and value-added tasks that require critical thinking and creativity. This shift increases efficiency and enhances job satisfaction, as employees feel more fulfilled when they engage in challenging and meaningful work (Schwarzmüller et al., 2018). Breevaart and Zacher (2019) suggest that automation significantly improves performance, particularly in industries such as manufacturing and mining, where operational processes are often labour-intensive.

Furthermore, DT equips employees with real-time data and analytics, enabling informed decisions and enhancing work accuracy (Corejova & Chinoracky, 2021). Employees equipped with advanced digital technologies are better able to perform their tasks efficiently, leading to increased JP and higher-quality outputs. For example, predictive analytics technologies allow employees to anticipate potential problems, make proactive adjustments, and optimise their workflows, thus minimising downtime and maximising productivity (Schallmo et al., 2017).

DT also enhances communication and collaboration within organisations, which is critical for improving JP. Digital platforms and technologies, such as project management software and instant messaging applications, facilitate seamless communication between team members, regardless of geographic location (Hanelt et al., 2021). This enhanced collaboration fosters teamwork and innovation, as employees can share ideas and collaborate on projects in real-time. Shujahat et al. (2019) suggest that when employees are better connected and have access to the information they need, their JP improves significantly

2.5.1.1 DT's Positive Impact on JP in Mining

Examples from the mining industry demonstrating that DT directly drives JP include Anglo American having employed IoT-enabled sensors to monitor critical equipment in real-time, enabling predictive maintenance and reducing unplanned outages (Ediriweera & Wiewiora, 2021). This proactive approach to maintenance not only reduces downtime but also enhances safety by minimising the need for human intervention in high-risk areas. Vale has used big data analytics to optimise ore processing, improve resource utilisation, reduce waste, and increase production efficiency (Zomer et al., 2020). Furthermore, by leveraging IoT and real-time data analytics, Vale's autonomous trucks and AI-powered predictive maintenance implementation have significantly improved resource allocation, operational efficiency and JP (Onifade et al., 2023). Similarly, Barrick Gold has integrated AI and ML algorithms into its exploration processes, significantly improving the speed and accuracy of identifying new mineral deposits. Employees now work alongside digital systems, improving decision-making and enabling workers to focus on critical tasks such as safety monitoring and strategic planning (Gruenhagen & Parker, 2020). These initiatives have led to measurable improvements in JP, validating Hypothesis 1.

2.5.1.2 DT's Negative Impact on JP in Mining

In contrast, a mid-tier platinum mining company in South Africa illustrates a scenario where DT did not enhance JP. The company sought to implement automation technologies similar to those used by industry giants like Anglo American and Rio Tinto, focusing on AI-driven predictive maintenance and autonomous haulage systems. Unfortunately, the initiative fell short of delivering the anticipated improvements in JP. A key factor was the disconnect between the DT efforts and the company's EE strategies (Lukić-Nikolić, 2023). Insufficient employee involvement in the transition led to substantial resistance and disengagement, with staff perceiving a threat to their job security. Consequently, inadequate DT implementation efforts resulted in stagnant JP (Kwon & Kim, 2020). This case underscores the importance of fostering engagement to ensure the success of DT initiatives in enhancing JP (Bakker & Demerouti, 2017; Alobidyeen et al., 2022).

2.5.1.3 Hypothesis 1: DT has a significant positive association with JP

In summary, DT drives JP by automating routine tasks, providing real-time data, and improving communication and collaboration. These factors enable employees to work more efficiently, make better decisions, and contribute more effectively to organisational goals. The example from Vale shows that, when properly implemented and aligned with workforce engagement, DT can significantly improve JP in the mining industry. An organisation succeeds by combining technology with comprehensive engagement strategies, enabling workers to embrace new technologies and enhance both task and contextual performance. Contrarily, the South African platinum mining company shows that without sufficient EE and preparation, DT can fail to deliver the expected improvements in JP, leading to disengagement and operational inefficiencies. These advancements foster greater productivity, innovation, and job satisfaction, supporting hypothesis 1, which states that **"DT has a significant positive association with JP".**

2.5.2 DT's Influence on EE

DT has emerged as a pivotal factor in enhancing EE, reshaping the way organisations interact with their employees and the work environment. DT involves the integration of digital technologies into all aspects of an organisation, fundamentally altering operational processes, employee roles, and workplace culture (Correani et al., 2020). As a result, this study's hypothesis 2 suggests that **"DT has a significant positive association with EE".** To understand to what extent this hypothesis holds, it is important to explore how DT influences engagement and the various factors that contribute to its success. In this context, understanding the extent to which DT influences EE becomes essential, especially as organisations adapt to rapid technological advancements and the shifting expectations of the workforce (L. Duque et al., 2020).

Recent research indicates that the implementation of digital technologies positively impacts EE by creating more dynamic and flexible work environments. Employees experience increased autonomy and control over their tasks, resulting in heightened motivation and job satisfaction (Hooi & Chan, 2023). For instance, organisations that utilise collaboration technologies and digital platforms allow employees to engage in meaningful interactions, fostering a sense of belonging and connection to the organisation (Breevaart & Zacher, 2019). The accessibility of information and the ability to communicate seamlessly across different platforms enhance collaboration and teamwork, thereby reinforcing engagement levels (Lukić-Nikolić, 2023).

Additionally, DT enhances job resources, which are critical for fostering engagement. By providing employees with modern technologies and resources, organisations empower them to perform their roles more effectively. Studies show that when employees feel equipped with the necessary technology and support, their engagement levels significantly increase (Macey & Schneider, 2008). This empowerment allows employees to focus on their strengths and contributions, which is vital for cultivating a proactive and engaged workforce (Buil et al., 2019).

Furthermore, DT facilitates more personalised and adaptive work experiences. With advancements in data analytics, organisations can tailor work processes to suit individual employee preferences and capabilities (Goswami & Upadhyay, 2019). This customised approach not only enhances employee satisfaction but also promotes a sense of ownership and commitment to organisational goals (Ye et al., 2024). Personalisation of work experiences aligns employees' strengths and interests with their roles, further increasing their engagement and productivity (Kwon & Kim, 2020).

2.5.2.1 DT's Impact on EE Through Empowerment and Autonomy

The Covid-19 pandemic has underscored the importance of DT as a driver of EE, particularly with the widespread adoption of remote work arrangements. The rapid implementation of digital technologies and platforms propels the shift to remote work, allowing employees to maintain productivity while working from home (Chatterjee & Rana, 2023). One of the primary ways in which DT positively influences EE is through the empowerment of employees. Digital technologies enable individuals to take more control over their tasks, providing greater autonomy in how they manage their work (Bakker & Albrecht, 2018). For example, cloud-based platforms and real-time data analytics allow employees to access information independently, make informed decisions, and complete tasks more efficiently. This autonomy fosters a sense of ownership and responsibility, leading to higher engagement as employees feel more connected to their work and the organisation's success (Buil et al., 2019).

The flexibility afforded by digital technologies further enhances DT's positive impact on EE through increased autonomy. In many industries, including sectors such as mining and manufacturing, DT enables remote monitoring and operation, providing employees with the flexibility to work remotely or in hybrid environments and facilitating effective communication, collaboration, and support (Hooi, 2021). This flexibility, particularly amplified by the Covid-19 pandemic, has improved work-life balance, a crucial factor in sustaining high levels of EE (Chatterjee, Rana, et al., 2021). Employees with the flexibility to manage their work and personal lives effectively are more likely to remain engaged and committed to their roles (Malhotra, 2021).

Remote working environments often present EE challenges, including feelings of isolation and disconnection from the organisation (Malhotra, 2021). However, organisations that invested in DT initiatives to enhance virtual collaboration reported increased EE levels (Alanizan, 2023). For example, videoconferencing technologies and instant messaging applications fostered a sense of community and connection, enabling employees to stay engaged with their teams and contribute to collective goals despite physical distances (Ye et al., 2024).

Furthermore, digital technologies facilitate work-life balance, which is crucial for sustaining EE in remote settings. By enabling flexible work hours and efficient communication channels, organisations empower employees to manage their work and personal lives more effectively. This flexibility fosters a sense of autonomy and control, leading to improved engagement and job satisfaction (Chatterjee, Rana, et al., 2021).

2.5.2.2 DT's Impact on EE Through Personalised Experiences

DT allows for more personalised work experiences by leveraging data analytics and AI to tailor tasks and responsibilities to individual strengths and preferences. This customisation not only improves efficiency but also enhances job satisfaction, as employees are more likely to feel valued and recognised when their roles align with their personal skills and career goals (Warner & Wäger, 2019). Job satisfaction is a key driver of EE, as it fosters a positive emotional connection between the employee and the organisation, reinforcing loyalty and commitment (Lukić-Nikolić, 2023).

Personalised work environments enabled by DT also facilitate continuous feedback and recognition, which are essential components of EE. Digital technologies such as performance management systems and feedback platforms allow managers to provide real-time feedback, helping employees stay informed about their progress and achievements. This continuous communication reinforces employees' sense of purpose and contribution, driving higher levels of engagement (Hooi & Chan, 2023). The constant feedback loop also empowers employees to improve their performance and align their efforts with organisational objectives, further solidifying their engagement (Macey & Schneider, 2008).

2.5.2.3 DT's Impact on EE Through Innovation and Collaboration

Another way DT positively impacts EE is by fostering a culture of innovation and collaboration. Advanced digital technologies facilitate communication and teamwork, allowing employees to collaborate across departments, geographies, and time zones more effectively. Collaboration technologies such as project management software, videoconferencing, and instant messaging create opportunities for employees to work together on projects, share ideas, and contribute to organisational innovation (Duque et al., 2020).

Collaboration encourages employees to feel more involved in the organisation's strategic goals, boosting their sense of belonging and emotional engagement. Studies have shown that employees participating in collaborative efforts are more likely to commit emotionally to their organisations (Breevaart & Zacher, 2019). In addition, DT empowers employees to experiment with new technologies and innovate within their roles, further enhancing their engagement. Employees encouraged to innovate often feel a greater sense of ownership and accomplishment, leading to improved motivation and dedication (Goswami & Upadhyay, 2019).

2.5.2.4 DT Impact on EE Through Training and Development

Training and development support hypothesis 2, suggesting an association between DT and EE. Organisations undergoing DT often invest in upskilling and reskilling programmes to ensure employee adaptation to new technologies (Alanizan, 2023). These training initiatives not only prepare employees for the technological demands of their roles but also signal that the organisation values their growth and professional development (Sung & Choi, 2018). Lukić-Nikolić (2023) indicates that when employees have opportunities for learning and development, they perceive that the organisation is investing in their future, and their engagement levels increase

Training initiatives linked to DT provide employees with the necessary competencies to thrive in a digitally transformed workplace, reducing feelings of job insecurity that may arise from the introduction of new technologies (Nam, 2019). When employees feel confident in their ability to use digital technologies effectively, they are more likely to embrace DT as an opportunity for growth rather than as a threat to their job security. This mindset contributes to higher engagement, as employees feel supported and empowered to succeed in a digital environment (Warner & Wäger, 2019).

2.5.2.5 DT's Impact on EE Challenges: Job Insecurity and Resistance

While the hypothesis that DT has a positive impact on EE holds strong, it is essential to acknowledge the potential challenges that may arise during DT initiatives. One of the primary concerns is the perception of job insecurity, as employees may fear being replaced by automation and AI-driven systems (Breque et al., 2021). This fear can lead to disengagement if not managed effectively, as employees may feel threatened by technological advancements. However, organisations that proactively address these concerns through transparent communication and comprehensive training programmes are more likely to mitigate these negative effects and maintain high levels of engagement (Lukić-Nikolić, 2023).

Resistance to change is another potential barrier to the positive impact of DT on EE. Some employees may struggle to adapt to new digital technologies, particularly if they are not adequately supported throughout the transformation process (Ye et al., 2024). Ensuring that employees are actively involved in the DT process, through feedback and participation in decision-making, can help reduce resistance and foster engagement (Buil et al., 2019). Organisations that prioritise inclusive and supportive transformation processes are more likely to see the positive effects of DT on EE, as employees feel more secure, empowered, and motivated to embrace technological change. Organisations must invest in training programmes that equip employees with the skills and confidence needed to navigate these changes, ensuring that they remain engaged and motivated throughout the transformation process (Warner & Wäger, 2019).

2.5.2.6 Hypothesis 2: DT has a significant positive association with EE

Digital technologies and processes improve employee autonomy, job satisfaction, collaboration, innovation, and professional development. DT enables organisations to create more flexible and personalised work environments, fostering higher levels of engagement and commitment, supporting hypothesis 2. However, to fully realise the positive impacts of DT on EE, organisations must carefully manage challenges related to job insecurity and resistance to change. By investing in training, providing ongoing support, and ensuring transparent communication, organisations can harness the full potential of DT to drive EE and, ultimately, organisational success.

2.5.3 The Role of EE in Enhancing JP

Research indicates that engaged employees perform better because of their heightened motivation, ownership of their work, and commitment to organisational goals (Albrecht et al., 2015). Engaged employees reflect positive emotional and cognitive connections towards their organisation (Kwon & Kim, 2020) and exert discretionary effort, going beyond basic job requirements, which enhances productivity and performance (Bakker & Albrecht, 2018; Shuck et al., 2017). They are more likely to collaborate, take initiative, and offer innovative solutions, contributing significantly to organisational success. Additionally, they exhibit higher resilience, enabling them to cope with job demands and adapt to workplace changes (Kwon & Kim, 2020).

Prioritising EE also reduces turnover. Engaged employees feel a strong connection to their organisation, making them less likely to leave, thereby reducing recruitment and training costs while preserving institutional knowledge (Breevaart & Zacher, 2019). Furthermore, EE fosters innovation, as engaged employees feel empowered to share ideas and take risks, promoting continuous improvement and organisational competitiveness (Shuck et al., 2017).

In resource-intensive industries like mining, where operational challenges are significant, fostering EE is essential for improving productivity and safety (Alobidyeen et al., 2022). Engaged employees align their personal goals with organisational objectives, fostering a shared sense of purpose that drives JP (Bailey et al., 2017). EE also enhances teamwork and collaboration, leading to more effective problem-solving and innovation, thereby increasing overall productivity (Schaufeli & Bakker, 2004). These dynamics demonstrate how EE plays a pivotal role in driving JP, particularly in demanding sectors like mining.

2.5.3.1 EE's Positive Impact on JP in Mining

In high-risk industries such as mining, where safety and operational efficiency are paramount, EE significantly influences JP. Companies that prioritise EE as part of their organisational strategies often experience enhanced performance, while neglecting engagement can lead to operational inefficiencies and safety risks (Saks & Gruman, 2021). For example, BHP has successfully leveraged EE within its "mine of the future" programme, which integrates automation and digital technologies. By focusing on EE, BHP has seen improvements in operational efficiency and safety outcomes. Similarly, Rio Tinto recognised that the success of its DT efforts was contingent on its workforce's engagement. The company invested in upskilling its employees, fostering a culture of continuous learning, and promoting collaboration and innovation (Marenge et al., 2014). By involving employees in the design and implementation of new technologies, Rio Tinto ensured high levels of engagement, resulting in substantial gains in productivity and operational efficiency (Jang & Topal, 2020; Onifade et al., 2023). These examples illustrate how effective EE strategies drive JP in the mining sector, particularly in the context of DT initiatives.

2.5.3.2 EE's Negative Impact on JP in Mining

Conversely, some mining companies have faced operational setbacks due to insufficient EE. For instance, a South African mining firm experienced high employee turnover and operational inefficiencies attributed to a lack of focus on EE. The company's rigid hierarchical management style, combined with limited opportunities for employee input, led to disengagement, especially among operational workers. This disengagement resulted in decreased JP and a notable decline in productivity (Bakker & Demerouti, 2017). This case highlights the critical importance of involving employees in organisational changes and fostering a culture of engagement to maintain sustained JP (Jiang & Men, 2017).

2.5.3.3 Hypothesis 3: EE has a significant association with JP

EE is a critical driver of JP in the mining sector and beyond. Engaged employees demonstrate higher levels of motivation, commitment, and discretionary effort, all of which contribute to improved JP (Bakker & Albrecht, 2018; Shuck et al., 2017). A growing body of evidence supports the hypothesis, particularly in industries like mining, where the demands on workers are high, and the risks associated with disengagement are significant. Companies that invest in fostering a culture of engagement through communication, training, and employee involvement see significant improvements in JP, while those that neglect EE often face challenges in achieving their operational goals (Bakker & Albrecht, 2018; Saks & Gruman, 2021).

2.5.4 Mediating Effects of EE on the DT-JP Relationship

2.5.4.1 EE as a Mediator of DT-JP Relationship

DT reshapes workplace dynamics, offering opportunities for innovation and flexibility that can boost EE and consequently influence JP. Engaged employees feel empowered to take ownership of their roles, exhibit greater motivation, and are more likely to adapt to new digital technologies and technologies, thereby improving JP (Goswami & Upadhyay, 2019; Schwarzmüller et al., 2018). EE serves as a mediator between DT and JP, amplifying the positive outcomes of DT when employees are actively involved in the transformation (Breevaart & Zacher, 2019).

In digitally transforming environments, EE is critical for the success of technological advancements. Engaged employees are more receptive to training and development opportunities, viewing new technologies as enablers rather than threats to job security (Bakker & Albrecht, 2018). This heightened engagement ensures employees integrate digital technologies effectively into their workflows, driving improved performance (Warner & Wäger, 2019). Conversely, disengaged employees may resist these changes, resulting in lower productivity and higher frustration levels (Correani et al., 2020).

In industries like mining, where DT often involves implementing complex technologies, EE plays a pivotal role in ensuring employees are willing and able to adapt. Engaged workers are more inclined to see DT as an opportunity for growth and innovation, contributing positively to JP and organisational outcomes (Duque et al., 2020). Thus, fostering EE is essential for leveraging the full benefits of DT to improve JP across the sector.

2.5.4.2 EE's Positive Mediating of DT-JP Relationship in Mining

Several companies within the mining sector have successfully leveraged EE to drive JP through DT. Rio Tinto, one of the world's largest mining corporations, stands as a leading example of how EE can facilitate a successful DT. Rio Tinto implemented its "mine of the future" initiative, which focused on automating mining operations and integrating AI and ML into daily processes. Rio Tinto, through extensive training and development programmes, ensured that its workforce was not only prepared for but actively engaged in the transition (Gruenhagen & Parker, 2020). The company provided continuous support to its employees, fostering a culture of collaboration and innovation. As a result, EE levels remained high, which directly contributed to improvements in JP. The use of autonomous trucks and AI-driven systems in its mining operations led to increased productivity, reduced costs, and enhanced safety, demonstrating the positive impact of DT on JP when prioritising EE (Barnewold & Lottermoser, 2020).

BHP, another global leader in the mining industry, has successfully leveraged DT to enhance EE and JP. By integrating advanced technologies such as AI and predictive analytics into its maintenance operations, BHP achieved significant reductions in equipment downtime while optimising overall operational efficiency. These technological advancements were complemented by robust workforce engagement strategies, ensuring that employees were integral to the transformation process (Jang & Topal, 2020).

Central to BHP’s approach was actively involving employees in decision-making processes and offering comprehensive training to equip them with the necessary skills to utilise new technologies effectively. This not only boosted productivity but also fostered greater job satisfaction and engagement, as employees felt valued and empowered to contribute meaningfully to the company's success (Sánchez & Hartlieb, 2020).

The integration of DT and EE has been a cornerstone of BHP’s DT. By creating an environment where employees are both engaged and skilled in using digital technologies, BHP demonstrated that aligning technological advancements with workforce engagement can yield substantial improvements in JP (Onifade et al., 2023). This approach emphasises the importance of prioritising EE to ensure the success of DT initiatives, particularly in high-demand and technology-driven sectors such as mining.

2.5.4.3 EE's Negative Mediating Impact on DT-JP Relationship in Mining

In contrast, disengaged employees may resist technological changes, which can result in operational inefficiencies and reduced productivity. Companies that neglect EE during DT risk experiencing reduced JP and failed initiatives (Lukić-Nikolić, 2023; Vial, 2019). Disengaged employees or lack of necessary resources to succeed in a digitally transformed work environment hinder DT efforts (Smuts & Van der Merwe, 2022). This highlights the importance of fostering a culture of engagement and providing employees with the technologies and training needed to thrive in a digital workplace (Nadeem et al., 2024).

A casing point is the failure of certain smaller mining companies to successfully adopt automation technologies. In some instances, the failure to engage employees effectively during the implementation of digital technologies led to resistance, disengagement, and ultimately, lower productivity (Vial, 2019; Lukić-Nikolić, 2023). For example, a mid-sized Australian mining company attempted to introduce AI-driven technologies for operational efficiency but failed to provide adequate training or support for its workforce. Employees, fearful of job displacement, resisted the new technologies and viewed the transformation as a threat rather than an opportunity for growth. The lack of engagement led to increased turnover, lower job satisfaction, and a decline in JP (Lukić-Nikolić, 2023).

2.5.4.4 The summary of the mediating role of EE between DT and JP

DT provides the technological foundation for improved efficiency, productivity, and innovation, but its success is largely dependent on the engagement and involvement of the workforce. When employees are actively engaged, they are more likely to embrace new digital technologies and technologies, leading to improved JP (Hanelt et al., 2021; Breevaart & Zacher, 2019). The examples of Rio Tinto and BHP illustrate how organisations that prioritise EE during DT see significant gains in productivity, job satisfaction, and overall performance. Conversely, companies that neglect engagement during DT efforts, such as the Australian mining company, often experience resistance, lower productivity, and failed initiatives. Therefore, this study illustrates how DT drives JP through EE, emphasising the need for organisations to foster a culture of engagement alongside their DT initiatives, supporting the hypothesis proposed by this study.

2.6 Literature Review Conclusion

This chapter has provided a comprehensive literature review exploring the key themes of DT, EE and JP within the SA mining sector. The review began by defining DT and examining its scope, with a focus on its application in the mining sector. It identified key digital technologies and the factors influencing DT, such as operational efficiency, workforce readiness, leadership, and regulatory pressures. This chapter also addressed the barriers to successful DT, including resistance to change and market challenges.

The discussion then moved to EE, defining the concept and outlining various frameworks, such as Kahn's engagement model and the job demands-resources (JD-R) model, which highlight the understanding of EE in different contexts. The chapter explored key factors influencing EE, including job satisfaction, organisational culture, leadership, and job resources, particularly within technology-driven environments like mining.

It then examined the importance of JP with a focus on task and contextual performance, and its relevance in the mining industry. The chapter further explored the interrelationship between DT, EE, and JP, presenting hypotheses on how DT impacts both JP and EE and how EE can act as a mediator in this relationship. The review demonstrated that while DT can enhance JP and EE by empowering employees, fostering innovation, and improving autonomy, it also brings challenges such as job insecurity and resistance.

Therefore, this chapter has established a strong theoretical foundation, outlining the relationships between DT, EE, and JP and providing the groundwork for the study's hypotheses. The next chapter delves into research model development based on the developed hypothesis to further investigate these constructs. Figure 8 shows the structure of the topics covered in this chapter.

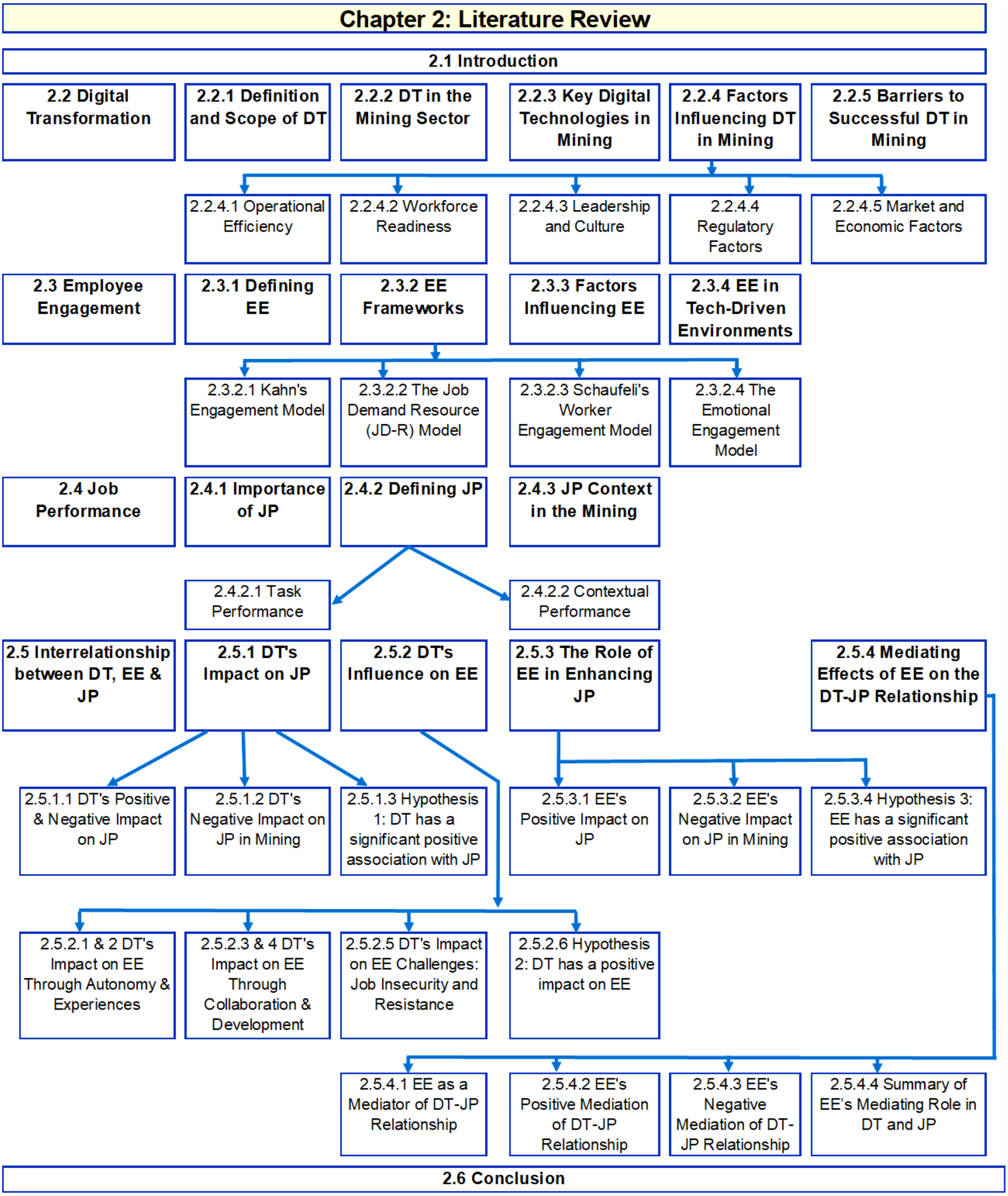

Figure 8: Literature review structure
Source: Author's illustration

3. Chapter 3: Research Model Development

3.1 Introduction

This chapter outlines the development of the research model, which serves as the foundation for investigating the relationships between DT, EE, and JP. The research addresses the primary question: **"To what extent does digital transformation impact individual employees' job performance in the South African mining industry?"** To address this question, the secondary question explores "**To what extent does employee engagement influence the relationship between DT and individual employees' JP in the South African mining industry?**" by examining the role of cognitive, emotional, and behavioural engagement in mediating this relationship.

The research model integrates three hypotheses: **(1) DT has a significant positive association with JP; (2) DT has a significant positive association with EE; and (3) EE has a significant positive association with JP.** By linking these constructs and their respective sub-dimensions, the model provides a comprehensive understanding of how digital technologies and EE drive JP in the mining sector. The chapter also aligns the model with relevant theoretical frameworks, establishing the conceptual basis for empirical testing in the later stages of the study.

3.2 Conceptual Framework

The conceptual framework builds on the interaction between DT, EE, and JP, suggesting that DT directly impacts both EE and JP and that EE acts as a mediating factor influencing JP. The model hypothesises that successful DT in an organisation enhances EE and improves JP. An instrument developed in peer-reviewed journals measured the DT construct. Validated scales measured EE and JP constructs, with each construct comprising three and two sub-constructs, respectively. The EE scale (EES) comprises psychological, cognitive and behavioural engagement, while the individual work performance questionnaire (IWPQ) scale comprises task and contextual performance.

3.2.1 Constructs of DT, EE and JP

3.2.1.1 JP Construct

DT involves integrating digital technologies within organisational processes to enhance efficiency, productivity, and innovation (Nasiri et al., 2020). The literature suggests that DT significantly reshapes work environments by providing advanced technologies and technologies that employees use to improve performance outcomes (Correani et al., 2020). This study posits that DT has direct associations with both EE and JP.

3.2.1.2 EE Construct

EE refers to how employees are psychologically and emotionally involved in their work. The three sub-constructs (i.e. cognitive engagement, emotional engagement, and behavioural engagement) adopted from the EES developed by Shuck et al. (2017) measure EE. The EES adopted in this study draws from Kahn's (1990) theory of personal engagement and disengagement, which posits that engagement is driven by psychological conditions of safety, availability, and meaningfulness at work. Additionally, Schaufeli's worker engagment model (2002) views engagement as a work-related state characterised by vigour, dedication, and absorption. Furthermore, it supports the alignment of the EES scale with contemporary engagement theory.

Cognitive engagement refers to the intellectual effort and focus employees apply to their tasks, encompassing problem-solving, information processing, and decision-making (Pincus, 2023). During DT, employees navigate innovations and new technologies, requiring heightened cognitive engagement. This form of engagement is essential for employees to align their existing skills with the evolving demands of DT, ensuring they remain adaptable and capable of effectively leveraging digital technologies (Kraus et al., 2022).

Emotional engagement reflects the affective bond employees feel towards their work, characterised by enthusiasm, passion, and commitment (Shuck et al., 2017). As organisations implement DT, emotionally engaged employees tend to view these changes more positively and are more willing to embrace new work processes, thereby enhancing their overall JP (Menges et al., 2023). This emotional connection plays a vital role in helping employees adapt to and thrive in environments transformed by digital advancements (Pincus, 2023).

Behavioural engagement is demonstrated through the actions and behaviours employees take to perform their duties, including the discretionary effort and proactive work behaviours they display (Menges et al., 2023). In the context of DT, behavioural engagement is crucial, as it influences employees' readiness to adopt new technologies, modify their work practices, and actively contribute to the successful implementation of digital strategies (Höyng & Lau, 2023). Employees who are behaviourally engaged are more likely to embrace innovation and support the success of DT initiatives (Menges et al., 2023; Meske & Junglas, 2021).

3.2.1.3 JP Construct

JP is commonly divided into two key sub-constructs: task performance and contextual performance, both of which are measured using the Individual Work Performance Questionnaire (IWPQ) (Koopmans et al., 2014). Task performance refers to the efficiency, accuracy, and effectiveness with which employees complete their core responsibilities, directly impacting organisational outcomes. Contextual performance, on the other hand, includes behaviours that go beyond formal job duties, such as teamwork, initiative, and adaptability, all of which contribute to a positive organisational environment (Chan et al., 2017).

3.3 Hypotheses Development

The research model has three key hypotheses, each positing a specific relationship between DT, EE, and JP, with four additional hypotheses positing specific relationships between EE and four control variables (i.e., age, educational level, job role and work experience). The hypotheses are based on existing literature and theoretical frameworks that suggest a strong connection between these constructs.

3.3.1 Hypothesis 1: DT has a significant positive association with JP

The first hypothesis proposes an association between DT and JP. By integrating advanced technologies such as AI, automation, and data analytics, DT enhances employees' ability to complete tasks with greater accuracy and efficiency, thereby improving task performance (Nasiri et al., 2020). These technologies streamline workflows, reduce redundancies, and provide real-time access to crucial information, which boosts overall productivity and innovation (AlNuaimi et al., 2022). Additionally, DT facilitates better collaboration and communication among employees, contributing to contextual performance by fostering behaviours that support a positive organisational environment (Ye et al., 2024). By improving both task execution and teamwork, DT aligns individual efforts with broader organisational goals, ultimately enhancing overall JP (Pincus, 2023).

3.3.2 Hypothesis 2: DT has a significant positive association with EE

The second hypothesis proposes an association between DT and EE. The relationship between DT and the three engagement states (i.e. behavioural, psychological, and cognitive engagement) is pivotal in understanding how technology-driven change influences employee performance. DT introduces new digital technologies, processes, and systems that can enhance behavioural engagement by empowering employees to adopt proactive and innovative actions in their work environments (Kraus, 2021). Psychologically, DT can strengthen employees' emotional connections to their roles, as technological advancements often lead to more meaningful and fulfilling work experiences, fostering higher job satisfaction (Ye et al., 2024). Cognitive engagement, on the other hand, is influenced by DT through the enhancement of problem-solving and critical thinking capabilities, as digital technologies streamline decision-making and data processing, allowing employees to engage more deeply with their tasks (Kline et al., 2024). Collectively, DT's impact on these three engagement states contributes to a more engaged, adaptive, and high-performing workforce.

3.3.3 Hypothesis 3: EE has a significant positive association with JP

The third hypothesis proposes an association between EE and JP. The relationship between JP and the three engagement states (i.e., behavioural, psychological, and cognitive engagement) is integral to understanding how engagement drives productivity and success in the workplace. Behavioural engagement enhances JP as employees demonstrate proactive actions, such as taking initiative and contributing beyond their basic job requirements, which directly impacts efficiency and outcomes (Saks, 2019). Psychological engagement fosters a deep emotional connection to work, motivating employees to invest greater effort, resilience, and commitment, thereby improving performance and reducing burnout (Lukić-Nikolić, 2023). Cognitive engagement relates to employees' deep mental investment in their tasks, with highly engaged employees focusing more on problem-solving, attention to detail, and innovation, all of which contribute to better overall JP. Thus, engagement leads to a more productive, efficient, and high-performing workforce, which benefits organisational success and individual job satisfaction (Perera et al., 2018).

3.4 Distributions of Key Constructs Across Demographic Characteristics

3.4.1 Age

Age significantly influences engagement with digital initiatives, as well as general engagement levels and JP. Younger employees, who often value career development and purpose-driven work, may exhibit higher openness and willingness to adapt to DT initiatives, which aligns with findings that younger generations often engage well with technologically forward roles (Aubert-Tarby et al., 2018). Mid-career professionals, typically aged 30-49, balance the need for stability with aspirations for growth, showing high cognitive engagement when given opportunities for skill advancement and autonomy (Shuck et al., 2017). In contrast, older employees may approach DT with caution, as they often prioritise job security and work-life balance. Research suggests they may benefit from tailored support, such as upskilling or mentoring, to mitigate resistance to DT and improve engagement (Ye et al., 2024). Providing age-sensitive engagement strategies like flexible training for older employees enhances participation and overall JP, ensuring employees across age groups feel invested in DT efforts (Aubert-Tarby et al., 2018).

3.4.2 Education level

Education level affects engagement with DT and overall job engagement and performance. Employees with advanced education levels typically display stronger cognitive engagement, as they often hold roles requiring greater autonomy and complexity, fostering motivation and adaptability (Bakker & Demerouti, 2017). These individuals are often better equipped to handle complex tasks and engage with new technologies, enhancing their performance in digital environments. Conversely, employees with lower educational backgrounds may encounter challenges in accessing growth opportunities, potentially leading to lower engagement, particularly if their roles lack stimulating challenges (Saks & Gruman, 2021). This differentiation underscores the importance of providing equitable opportunities for growth and adaptation to DT, regardless of educational background. Tailoring training and DT initiatives to meet the diverse needs of employees can increase engagement, enabling all individuals to embrace DT with confidence and contribute effectively to organisational goals (Kwon & Kim, 2020).

3.4.3 Job Role

Job role significantly influences engagement with DT, EE, and JP due to varying levels of decision-making and autonomy involved. Employees in leadership or specialist roles generally exhibit higher engagement and adaptability with DT because their tasks often involve strategic and knowledge-based responsibilities that align closely with DT objectives (Bakker & Demerouti, 2017). These roles require strong cognitive engagement, as problem-solving and decision-making responsibilities foster enthusiasm for DT initiatives and drive performance improvements (Buil et al., 2019). In contrast, operational or routine roles may lack the variety and complexity needed to sustain high engagement, especially when tasks are repetitive and offer limited opportunities for professional growth (Kwon & Kim, 2020). Recognising these role-based differences, organisations can enhance EE by actively involving employees across all functions in DT initiatives, fostering inclusivity and ensuring all roles are valued and aligned with digital transformation efforts (Saks & Gruman, 2021).

3.4.4 Work Experience

Work experience plays a pivotal role in determining engagement levels and responses to DT. Experienced employees often exhibit higher levels of confidence and emotional investment due to their familiarity with organisational processes, which bolsters both cognitive and emotional engagement (Breevaart & Zacher, 2019). This group tends to demonstrate greater resilience in adapting to DT, particularly when supported by continuous learning opportunities. Conversely, less experienced employees, especially those newer to their roles, may face challenges in adjusting to new technologies, requiring additional training to achieve similar engagement levels (Albrecht et al., 2015). By offering targeted development opportunities tailored to employees' experience levels, organisations can foster a workforce capable of adapting to DT, ensuring equitable engagement and performance outcomes across all experience brackets (Bakker & Demerouti, 2017).

3.5 Conceptual Model Presentation

The conceptual model for this study in Figure 9 illustrates the relationships between the three constructs (i.e., DT, EE, and JP).

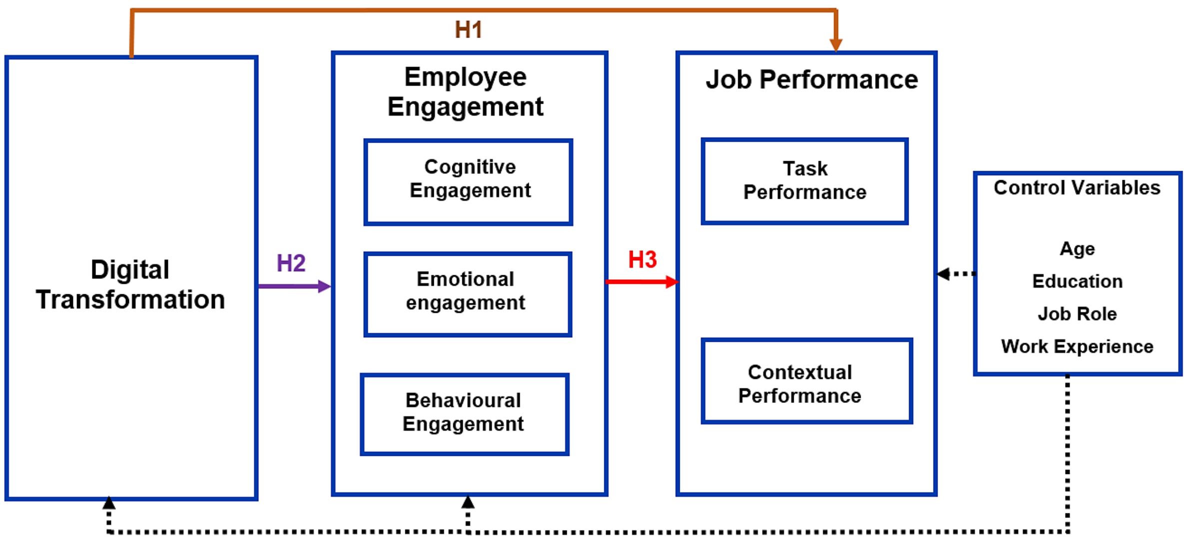

Figure 9: Proposed research model
Source: Author's illustration

The model incorporates the sub-dimensions of EE and JP to provide a structured approach for evaluating the influence of DT. By integrating the three hypotheses, it creates a unified framework to explore how DT impacts engagement and performance outcomes.

In this model, hypothesis 1 proposes a direct association between DT and JP, suggesting that DT may lead to improved task and contextual performance. Hypothesis 2 asserts that DT positively impacts EE, which comprises cognitive, emotional, and behavioural engagement. Hypothesis 3 proposes that EE mediates the relationship between DT and JP, suggesting that engaged employees are more likely to experience improvements in task and contextual performance because of DT. Therefore this study investigates the associations between the control variables (i.e. employee age, education level, job role, and work experience) and its key constructs (i.e. DT, EE and JP).

3.6 Research Model Development Chapter Conclusion

The research model aligns with established theories of EE and JP. Kahn's (1990) theory of personal engagement and Schaufeli's worker engagement model (2002) support the EE construct and correlate with the JD-R framework, highlighting the significance of psychological, emotional, and behavioural engagement in enhancing JP. The IWPQ scale (Koopmans et al., 2014) provides a robust framework for measuring task and contextual performance, ensuring that the research captures the multifaceted nature of JP.

This chapter presents a clear conceptual model that links DT, EE, and JP with three supporting hypotheses. By exploring the interplay between these constructs, the research provides valuable insights into how DT influences EE and JP, particularly in the context of the South African mining sector. The next chapter delves into the research methodology used to test these hypotheses and further investigate these constructs.

4. Chapter 4: Research Methodology

4.1 Introduction

This chapter outlines the research methodology used to examine the relationships between DT, EE, and JP in the South African mining sector, as illustrated in Figure 10. It first details the research design and philosophy, highlighting the study's purpose, positivist approach, and deductive reasoning. The chapter then discusses the mono-quantitative method, research strategy, and time horizon. It covers the study setting, target population, sampling strategy, and unit of analysis. The chapter also introduces the measurement instruments for the constructs and explains data collection through a structured survey. Finally, it addresses data preparation, validation, analysis, and statistical methods, concluding with the study's limitations.

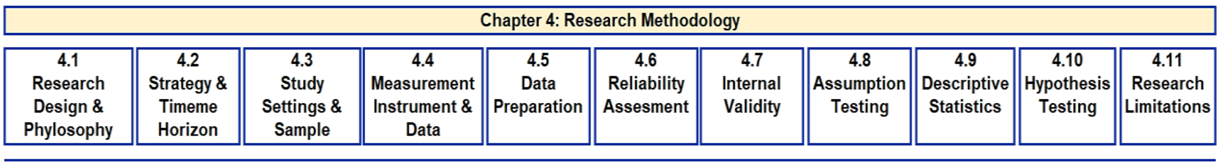

Figure 10: Chapter 4 roadmap
Source: Author's illustration

4.2 Research Design and Philosophy

This study employed a correlational research design to explore the relationships between DT, EE, and JP through individual-level data collection via a survey. The research identified statistically significant correlations between these constructs, aligning with the goal of hypothesis testing based on established theories (Creswell & Creswell, 2020). It followed a quantitative approach consistent with positivist research philosophy, emphasising objective measurement and statistical analysis (Saunders et al., 2019) as shown in Figure 11.

Participants completed the survey in a non-contrived setting, ensuring external validity by avoiding researcher interference (Bell et al., 2019). The unit of analysis comprises individual respondents, focusing on their perceptions of DT, EE, and JP (Quinlan et al., 2019). The research adopted a cross-sectional time horizon, collecting data at a single point to assess the relationships between constructs (Bryman, 2021). A structured sampling design ensured representative data, while a standardised survey instrument provided consistent measures (Saunders et al., 2019). Correlation and regression analysis tested the hypotheses and offered empirical support for the proposed relationships (Hair et al., 2020).

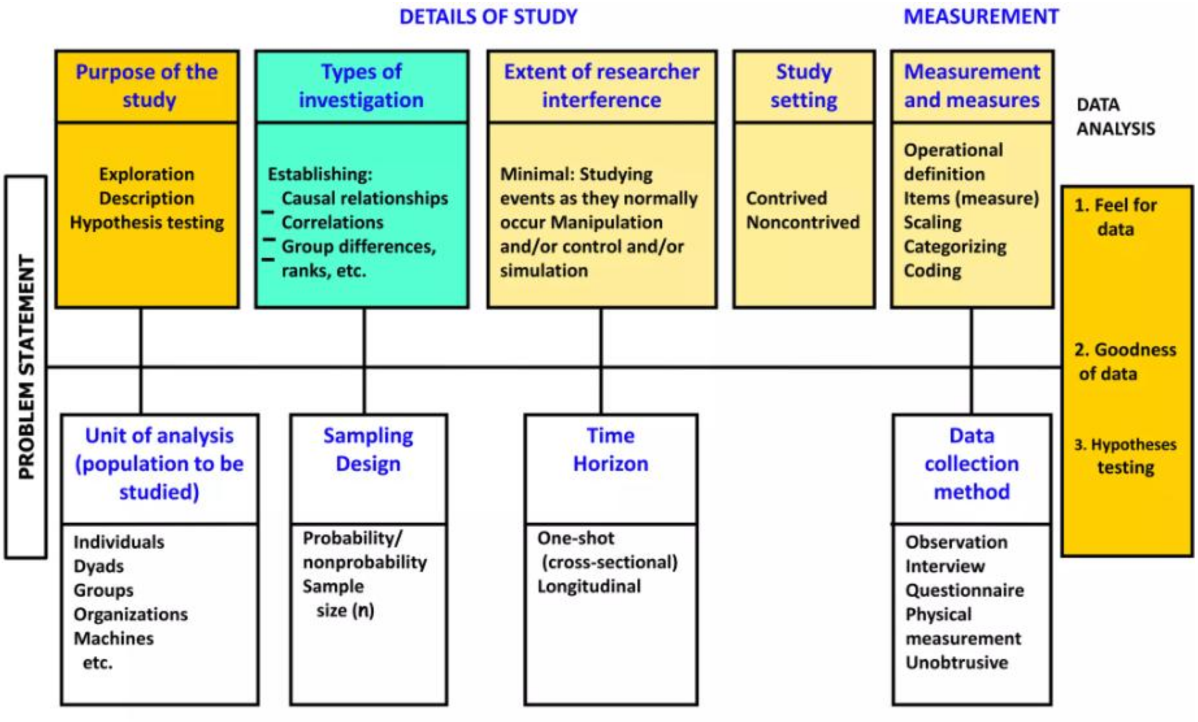

Figure 11: Research design schematic
Source: Adapted from Sekaran & Bougie, 2010, p. 34

4.2.1 Philosophy of the Study

The research adopted a positivist epistemological approach, focusing on discovering measurable facts and patterns that lead to credible data. Aligned with the stance of natural scientists, the study works with observable social realities to generate generalisable findings akin to scientific laws. Positivism relies on an empiricist method, using observable and measurable data to explain relationships between variables, without the influence of human interpretation or bias (Saunders et al., 2019). This approach suits the study's survey method, as it captures quantifiable data and supports replication. Emphasising statistical analysis allowed the researcher to derive generalisable conclusions from the collected data (Saunders et al., 2019).

4.2.2 Research Approach

This study employed a deductive research method to test hypotheses derived from established theories on the relationships between DT, EE and JP. The research examined whether the data collected supported or refuted the proposed hypotheses. This approach focused on measurable variables and used statistical analysis, allowing the study to contribute to the existing body of knowledge while exploring new insights into how these constructs interact (Quinlan et al., 2019). The deductive method is particularly suitable for hypothesis testing as it provides a structured way to analyse relationships between variables, offering clear evidence that can either validate or challenge current theories (Sekaran & Bougie, 2019).

This research aligns with a top-down deductive approach, starting with existing literature and theories related to DT, EE, and JP, and then formulating hypotheses to be tested through data collection. Standardised questions were used to gather quantitative data, ensuring consistency and enabling statistical analysis to test the relationships between the constructs (Creswell & Creswell, 2020). The deductive approach ensures the research is rooted in well-established theoretical frameworks, making the findings more generalisable and applicable to real-world contexts. By confirming or rejecting the hypotheses, this study contributes to refining or expanding the current understanding of the interplay between DT, EE, and JP, particularly in sectors undergoing rapid technological change (Saunders et al., 2019).

4.2.3 Methodological Choice

In line with the positivist philosophy, this study utilised a mono-quantitative research method to examine the relationships between three constructs, gathering individual data through a single structured data collection technique (i.e. survey). It involves consistent analysis of the hypotheses, providing statistically validated insights into the relationships between the constructs and ensuring a focused investigation of the research questions (Saunders et al., 2019). This method quantifies relationships between variables, providing empirical evidence based on numerical data, which enhances the rigour and precision of the findings (Hair et al., 2020). Its specificity and replicability make it widely applicable across various disciplines (Field, 2018; Creswell, 2014).

Aligned with the positivist philosophy, the mono-quantitative method leverages structured surveys to collect standardised data, enabling statistical analysis to identify correlations between the constructs. This objectivity and emphasis on replication allow for generalisable conclusions (Quinlan et al., 2019; Field, 2018). The structured data collection and statistical focus minimise researcher bias, supporting the validity of the results (Creswell, 2014).

4.3 Research Strategy and Time Horizon

4.3.1 Research Strategy

This study employed a survey-based research strategy to gather individual-level data, aligning with its objective of examining the relationships between DT, EE, and JP. Surveys are well-suited for studies seeking to quantify attitudes, behaviours, and perceptions across large populations, allowing for the efficient collection of standardised data (Creswell & Creswell, 2020). The structured nature of surveys facilitates statistical analysis, enabling the researcher to test hypotheses and establish correlations between the constructs (Saunders et al., 2019). In addition, the survey design supports the cross-sectional time horizon adopted in this study, providing a snapshot of participants' views at a single point in time (Bell et al., 2019). The survey included validated measurement instruments for each construct, ensuring the reliability and validity of the data collected (Shuck et al., 2017; Koopmans et al., 2014). By employing this method, the study ensures a robust framework for evaluating the influence of DT on JP, as mediated by EE, within the South African mining industry.

4.3.2 Time Horizon

This study employed a cross-sectional time horizon to examine the relationships between the three constructs through a survey, collecting data at a single point in time (Saunders et al., 2019). This approach provided a snapshot of participant responses, allowing for the analysis of the constructs and their interrelationships based on data reflective of that specific moment (Bell et al., 2019). Cross-sectional studies are effective for identifying correlations between variables, as they enable the collection of large volumes of data within a short time frame, focusing on statistical analysis and generalisability (Creswell & Creswell, 2020). Unlike longitudinal studies, which require extended data collection to observe changes over time, the cross-sectional design captures a single set of measurements, aligning with the study's aim of identifying immediate relationships between the constructs (Bryman, 2021; Quinlan et al., 2019). This approach ensures efficient data collection and analysis, fitting within the study's quantitative research framework (Saunders et al., 2019).

4.4 Study Setting and Sample

4.4.1 Study Setting

The study focuses on the South African mining industry, a major contributor to South Africa's economy. The mining industry offers a dynamic environment for exploring key constructs such as JP, EE, and DT. The study spans diverse organisational contexts, from large multinational corporations to smaller local companies, providing insight into varying workplace cultures and practices that may influence worker perceptions and behaviours (Dayo-Olupona et al., 2023). It collected data through an anonymous online survey, ensuring broad participation and candid responses across different organisations. This setting enables a comprehensive examination of the relationships among the constructs, offering valuable insights into how knowledge workers perceive their roles and navigate the changing landscape of the mining industry (Smuts & Van der Merwe, 2022).

4.4.2 Target Population

The target population for this study comprises knowledge workers within the South African mining industry. Knowledge workers are individuals whose primary job involves creating, processing, and applying knowledge, which is essential to the functioning of complex industries such as mining (Vuori et al., 2019). This study defines knowledge workers as employees directly affected by DT and utilise computers to execute their daily tasks. To ensure the accuracy and relevance of the data collected, the survey questionnaire included screening questions designed to verify that participants were indeed knowledge workers within the sector. This step was crucial in maintaining the validity and reliability of the research findings, as it ensured that only those directly involved in the knowledge-intensive functions of the mining industry were included in the sample (Dayo-Olupona et al., 2023). By focusing on this specific target population, the study aligned with its primary objective of investigating the relationship between DT, EE, and JP in a relevant and highly specialised professional context.

4.4.3 Sample Size

The sample size is crucial for conducting robust inferential statistical analysis. An inadequate sample reduces the ability to generate meaningful insights, making findings unreliable (Köhler et al., 2017). A small sample limits statistical significance and generalisability (Hair et al., 2019). Determining the appropriate sample size depends on factors like the number of questions, response variability, and statistical techniques used (Field, 2018). A general guideline recommends 5 to 10 respondents per question for sufficient statistical power (Hair et al., 2020). For the 30-item questionnaire in this study, a sample size of 150-300 respondents is recommended to ensure valid and reliable analysis through methods like regression and correlation.

In addition to following general guidelines, power analysis plays a crucial role in determining the sample size. Power analysis evaluates the probability of correctly rejecting a null hypothesis and is influenced by factors such as effect size, significance level, and the desired power (Zurakowski & Staffa, 2023). A common benchmark for social science research is a power level of 0.80, with a medium effect size and a significance level of 0.05 (Creswell & Creswell, 2018). Based on these parameters, G*Power software Lakens (2022) and (Hair et al., 2020) suggests a minimum sample size of approximately 150 respondents for robust results. Therefore, a sample size between 150 and 300 participants is appropriate, ensuring sufficient statistical power for data analysis.

4.4.4 Generalisability

Generalisability refers to the extent to which research findings can be applied to a broader population (Saunders et al., 2019). Although convenience sampling was employed, this study minimised bias by targeting a diverse group of knowledge workers across various South African mining companies. Broad distribution methods, such as LinkedIn, direct emails, and social media, helped reach a more representative sample, improving external validity (Williams, 2020). This broad approach enhances the ability to generalise findings to the wider population of knowledge workers in the mining sector. However, while these steps strengthen representativeness, some limitations remain due to the inherent nature of non-probability sampling (Saunders et al., 2019). Despite this, the methodological rigour applied ensures the study's findings are robust and relevant to the industry.

4.4.5 Unit of Analysis

The unit of analysis for this study is the perceptions of individual knowledge workers within the South African mining industry. This focus enables a detailed examination of their roles, experiences, and perceptions regarding the key constructs under investigation. Analysing individual responses allows for the identification of patterns and relationships between the constructs, enhancing the validity of the research findings (Saunders et al., 2019).

Knowledge workers play crucial roles in mining, where expertise and decision-making significantly impact organisational outcomes. These professionals contribute to knowledge creation and application (Vuori et al., 2019), making them ideal subjects for examining DT, EE and JP.

Focusing on individuals allows for robust statistical analysis, such as regression and correlation, to uncover significant relationships between variables (Field, 2018). This approach aligns with best practices in survey research, emphasising the value of individual perspectives in shaping organisational strategies (Shujahat et al., 2019). By centring on knowledge workers, the study ensures that its findings are relevant and practically applicable to the mining industry.

4.5 Measurement Instruments and Data Collection

4.5.1 Survey Questionnaire

This study developed an online survey questionnaire using the Qualtrics platform, comprising 30 questions that addressed the constructs of interest: DT, EE, and JP, alongside additional biographical information. Thereafter, it operationalised close-ended survey questions into measurable items, each with specific answer choices for ease of analysis (Hair et al., 2020). This ensured alignment with the underlying theoretical framework. Pretesting the questionnaire, which included three measuring instruments, enhanced clarity and suitability before implementation (de Vaus, 2022).

The design featured clear, concise questions that prioritised data protection and participant anonymity. The researcher modified certain questions to avoid bias and ensure an accurate representation of respondents' views (Kock et al., 2021). Screening questions confirmed that participants were knowledge workers in the mining sector, thus maintaining the validity of the findings. The study communicated its purpose to participants, obtained informed consent, and included an introductory cover letter outlining participation procedures and data handling (see Appendix 1). To prevent respondents from predicting causal relationships, the survey grouped questions by constructs (i.e., DT, EE, and JP), ensuring reliability and validity in data collection (Hair et al., 2020; Saunders et al., 2019).

4.5.2 Measurement Instruments

The measurement instruments section details the technologies employed to evaluate the key constructs in this study: DT, EE, and JP. To ensure robustness, the study incorporates validated scales from previous research, adapting them to suit the specific context. The chosen scales demonstrated effectiveness in similar settings, ensuring alignment with the study's goals. By using established instruments, the research upholds the reliability and validity of the data (Hair et al., 2020).

The following sub-sections offer an in-depth examination of the instruments used for measuring DT, EE, and JP, highlighting their significance to the research question (Saunders et al., 2019). As poised by Boateng et al. (2018) the researcher standardised the instruments, employing closed-ended survey questions with a 5-point Likert scale (1 = strongly disagree, 2 = disagree, 3 = neither agree nor disagree, 4 = agree, 5 = strongly agree) to maintain consistency.

4.5.2.1 DT Measurement Instrument

The DT instrument comprises five questions, each representing a variable or sub-construct, as shown in Appendix 1. Adopted from rigorously validated studies (AlNuaimi et al., 2022; Nasiri et al., 2020), this tool captures the multifaceted nature of DT, which affects processes, structures, and employee behaviours. By using a validated instrument, the study ensures accurate measurement of DT, offering insights into how digital technologies influence JP and EE. The questions assess critical areas, including technology adoption, integration into daily operations, and strategic use of data, ensuring a holistic approach that provides valid and reliable data for analysis.

4.5.2.2 JP Measurement Instrument

The Individual Work Performance Questionnaire (IWPQ) consists of 13 questions, capturing key dimensions of JP (see Appendix 1). This study focuses on task and contextual performance, excluding counterproductive behaviour. Task performance measures efficiency and quality in core tasks, while contextual performance involves behaviours supporting the organisational environment, such as collaboration and innovation (Ramos-Villagrasa et al., 2019; Koopmans et al., 2014). The IWPQ, validated through various tests, is reliable across industries (Koopmans et al., 2014). Its use is critical for assessing both tangible outcomes and behaviours that contribute to long-term success, allowing a nuanced analysis of how DT and EE impact individual JP.

4.5.2.3 EE Measurement Instrument

The Employee Engagement Scale (EES), presented in Appendix 1, consists of 12 questions measuring cognitive, emotional, and behavioural engagement. This study uses the 12-item version by Shuck et al. (2017), which offers a holistic assessment of EE in modern workplaces. Cognitive engagement gauges employees' mental focus, emotional engagement assesses their positive emotional connections to work, and behavioural engagement measures their actions and dedication. The validated EES ensures a comprehensive understanding of how engagement drives JP, particularly in the context of DT. Its proven reliability across industries ensures credible findings, making it a valuable tool for examining EE's impact on JP.

4.5.3 Data Collection

This study collected individual-level data on the three constructs through an online survey administered on the Qualtrics platform, known for its reliability and commitment to respondent anonymity. After defining the target population, the researcher used convenience sampling to access participants from various organisations in the South African mining sector. The researcher upheld ethical standards throughout the process, ensuring participant anonymity (Choi et al., 2019).

To maximise response rates, the researcher employed a multi-channel distribution strategy, sharing the survey link with over 2,800 LinkedIn followers, 2,500 direct LinkedIn contacts, and over 600 mining professionals via email. WhatsApp was also used to enhance accessibility, effectively leveraging social media to gather responses from a diverse sample of knowledge workers across different company sizes (Saunders et al., 2019). This effort yielded 627 responses, representing a robust dataset.

The researcher exported the survey data from Qualtrics to MS Excel, ensuring compatibility and data integrity while addressing any missing values or transfer errors (Hair et al., 2020). The researcher securely stored the raw data on Google Drive and a local backup drive, meeting the university's requirement for retaining research data for a minimum of ten years. This dual storage approach ensures both data security and long-term availability.

4.6 Data Preparation

4.6.1 Data Preparation and Coding

Upon exporting the data into MS Excel, the preparation process began by addressing inconsistencies such as duplicates and incomplete responses, following established protocols to ensure data integrity (Field, 2018). Initially, the dataset comprised 627 survey responses, but this decreased to 400 after eliminating incomplete entries, duplicates, and responses from individuals who were either non-knowledge workers or not employed in the mining industry. Despite this reduction, the remaining sample size of 400 still exceeded the minimum threshold of 300, necessary for achieving sufficient statistical power (Hair et al., 2020). Of the 30 survey questions used to measure DT, EE, and JP, each containing the final 400 selected responses, 11 questions had one missing value each, resulting in a completion rate of 399 out of 400 for these items. After calculating the mean, mode, and median for all construct items, the researcher observed a close alignment between the mode and median values. Following best practices in handling missing data, which recommend substituting missing values with the mode when data distributions exhibit minimal variability or strong central tendencies (Pallant, 2020; Hair et al., 2019; Field, 2018), the researcher opted to replace the 11 missing values with their respective mode values.

After cleaning the data in MS Excel, the researcher coded it in a sequential structure, with variables organised under their corresponding constructs (DT, EE, and JP) and thereafter exported it into SPSS for final coding (i.e., labelling variables, their values and measurements) as shown in Appendix 2. This ensured clarity and facilitated efficient navigation during analysis, as well as a solid foundation for examining relationships between variables (Pallant, 2020). The researcher categorised variables and defined appropriate measurement scales, such as ordinal or interval, to ensure the application of correct statistical analysis methods (Field, 2018). Coding categorical responses into numerical values further enabled the smooth application of statistical tests. Structuring the dataset accurately prepared it for correlation and regression analyses, ensuring reliable exploration of the relationships between the constructs ts (Pallant, 2020; Hair et al., 2021). These steps were pivotal in maintaining data integrity and ensuring meaningful results.

4.7 Reliability Assessment

The study assessed the reliability of the scales used to measure the constructs. Shuck et al. (2017) explains that reliability is about ensuring that the instrument produces consistent results under similar conditions, which is essential before any further analysis can reliably interpret those results in terms of validity. Without reliability, validity assessments may be misleading, as an unreliable measure cannot accurately capture the true characteristics of a construct, even if it appears to measure the right content on the surface. Hair et al. (2019) reinforce that reliability is a prerequisite for validity because consistency in measurement is essential before establishing the construct's relevance and alignment with theoretical frameworks. This study assessed the constructs' reliability measurements by calculating Cronbach's alpha to evaluate internal consistency, ensuring that the survey items reliably measured their respective constructs (Saunders et al., 2020). A Cronbach's alpha value of 0.7 or higher is generally considered an indicator of acceptable internal consistency, suggesting that the items within each construct measure a cohesive concept. Social science research widely uses this threshold to ensure that construct items align well with one another, enhancing the instrument's reliability (Taber, 2018; Ursachi et al., 2015).

The reliability assessment results for the constructs DT, EE, and JP show a high level of internal consistency across all items. Cronbach's alpha values for each construct exceed the commonly accepted threshold of 0.7 (Pallant, 2020; Hair et al., 2019). This indicates that the items within each construct reliably measure the intended concepts. Additionally, item-total correlations fall within acceptable ranges, further confirming that individual items contribute meaningfully to the overall reliability of their respective constructs (Field, 2018). These findings provide robust evidence of the constructs' reliability, ensuring that the survey measures are consistent and dependable for further analysis.

4.8 Constructs Validity

4.8.1 Confirmatory Factor Analysis

The study did not perform Confirmatory Factor Analysis (CFA) as it requires sophisticated software tools such as AMOS within the SPSS environment, which was not available for this research (Hair et al., 2021). Researchers typically employ CFA to validate the measurement model by testing the hypothesised relationships between observed variables and latent constructs, a process that requires advanced statistical software for accurate implementation (Brown, 2015). As an alternative, the study utilised Pearson correlation analysis for each construct to establish the relationship between variables, ensuring that individual teams contributed significantly to the construct under investigation. Researchers often use Pearson's correlation method when seeking to determine the strength and direction of linear relationships between continuous variables (Cohen et al., 2013). This approach, while less complex than CFA, provided sufficient insight into the construct validity by revealing the extent of inter-team consistency and contribution (Field, 2022). The use of correlation analysis was deemed an appropriate alternative given the study's available resources and its focus on exploring initial relationships rather than confirming the structure of constructs through advanced modelling techniques (Hair et al., 2021).

4.8.2 Pearson's Correlation Analysis

The study employed several validation techniques to ensure the survey measures were both accurate and relevant, focusing on content and construct validity. To ensure content validity, the researcher used established survey instruments aligned with the literature, verifying that the survey covered all critical aspects of the constructs while excluding irrelevant or misleading questions (Boateng et al., 2018). This process ensured the survey items were comprehensive and accurately reflected the theoretical frameworks guiding the research.

The study assessed construct validity using bivariate analysis through Pearson correlation, a method well-regarded for evaluating the relationships between variables and confirming whether items within a construct correlate significantly with one another (Hair et al., 2019). Pearson correlation specifically provides insight into how well items within each construct align, thus serving as an indicator of convergent validity, where highly correlated items suggest that they measure the same underlying construct (Tabachnick & Fidell, 2019). High correlations among items within the constructs of DT, EE, and JP indicate cohesive internal alignment, reinforcing the validity of these constructs within the study (Field, 2018). Pearson correlation also helps assess the discriminant validity by checking that items from different constructs have weaker correlations, ensuring that each construct remains distinct and accurately represents unique aspects of the study's theoretical framework (Kline, 2016).

4.8.3 Exploratory Factor Analysis (EFA)

Following the bivariate analysis, the study implemented an exploratory factor analysis (EFA) to reduce component variables, where applicable, and to determine the underlying structure of the constructs measured. EFA serves as a robust tool for identifying latent factors within a dataset by grouping correlated variables, thereby simplifying the model and enhancing interpretability (Tabachnick & Fidell, 2019). This method allows for a more concise representation of the constructs by ensuring that only relevant items that load significantly onto respective factors remain in the analysis. Through principal component analysis with varimax rotation, the study identified the primary components contributing to each construct, aligning with standard practice for achieving clearer and more interpretable factors. This reduction step ultimately refined the constructs, ensuring that further statistical analyses would focus on the most relevant indicators (Hair et al., 2019).

4.9 Assumption Testing

Assumption testing verifies that key statistical assumptions hold before further analysis, ensuring that conclusions drawn from the data are valid and reliable. This study tested two core assumptions (i.e. normality and homoscedasticity), given their importance in validating the use of various statistical techniques (Hair et al., 2019). Violations of these assumptions can lead to biased estimates and inaccurate results, particularly with parametric tests (Pallant, 2020). Thus, the assumption testing process was essential in guiding the study's selection of appropriate methods for hypotheses testing and assessing the robustness of statistical findings.

4.9.1 Normality Test

Normality testing is crucial when using parametric tests, as they assume that the data distribution approximates a normal curve, with values symmetrically distributed around the mean. This study examined normality using both visual inspections on histograms and Q-Q plots, including the Shapiro-Wilk and Kolmogorov-Smirnov tests, known for their sensitivity to non-normality (Field, 2018). These tests showed significant deviations from normality across key constructs, suggesting that the data does not follow a normal distribution. Consequently, the study employed non-parametric tests, such as Spearman's Rank and Kendall's Tau correlations, to maintain result validity by better accommodating the skewed data distributions (Cohen et al., 2013).

4.9.2 Homoscedasticity Test

Homoscedasticity, or the assumption that data variance remains constant across values of an independent variable, is critical for accurate regression analysis. The study tested for homoscedasticity by examining scatterplots of standardised residuals and predicted values, which is a commonly recommended approach (Hair et al., 2019). Additionally, statistical tests, including the modified Breusch-Pagan test, were used to confirm visual interpretations. Results revealed heteroscedasticity, which further supported the use of non-parametric analyses, as they are less sensitive to this assumption (Pallant, 2020). The study maintained rigorous standards for statistical testing by ensuring appropriate management of these assumptions.

4.10 Descriptive Statistics

Following assumption testing, the study generated descriptive statistics for both construct and demographic data. Descriptive analysis provided foundational insights into the dataset, highlighting central tendencies, variances, and distribution characteristics across key variables like age, job role, and work experience (Field, 2018). Additionally, descriptive statistics clarified the demographic composition of the sample, which informed subsequent analyses by identifying potential demographic influences on DT, EE, and JP. This step served as a preliminary investigation, ensuring a comprehensive understanding of the dataset before more advanced hypothesis testing.

4.11 Hypotheses Testing

4.11.1 Generalised Linear Model (GLM)

Given the data's non-normality, the study employed a generalised linear model (GLM) as a flexible, non-parametric method to test relationships between constructs. GLM allowed for the comparison of outcomes across multiple predictor variables, with results corroborated by additional non-parametric tests to ensure consistency (Hair et al., 2020; Tabachnick & Fidell, 2019). This approach helped confirm the robustness of the findings and ensured alignment with the study's theoretical framework.

4.11.2 Spearman's Rank and Kendall's Tau Correlations

The study conducted both Spearman's Rank and Kendall's Tau Correlations to assess relationships between constructs. These non-parametric methods are valuable for measuring association without assuming normality, and both tests yielded similar patterns of correlations across the constructs (Pallant, 2020). However, the study prioritised Kendall's Tau because of its more conservative estimates, thus minimising the risk of overestimating relationships and enhancing result reliability (Field, 2018).

4.11.3 Kruskal-Wallis Test

Finally, the study employed a Kruskal-Wallis test to explore variations in constructs like DT, EE, and JP across demographic variables, including age, education level, job role, and work experience. As a non-parametric alternative to one-way ANOVA, Kruskal-Wallis is appropriate when data does not meet parametric assumptions (Pallant, 2020). This test provided insights into whether demographic factors significantly influenced key constructs, guiding recommendations for demographic-sensitive engagement and development strategies in DT contexts (Hair et al., 2019).

4.12 Research Limitations

The research limits stem from the type and method of investigation (Saunders & Lewis, 2019). This research has the following limitations:

1. **Research philosophy and strategy:** The reliance on survey methodology can introduce self-reporting biases, such as social desirability bias, where respondents provide socially acceptable rather than genuine answers (Kock et al., 2021). Predetermined response options may also limit the depth of data, preventing respondents from fully expressing their experiences. This approach may miss crucial insights or underlying reasons for behaviours or attitudes (Bryman, 2021; Saunders et al., 2020). Combining quantitative and qualitative methods would offer richer, more contextual data, enhancing the research's depth beyond what fixed responses can capture (Creswell & Creswell, 2020).

2. **Methodological choice:** The mono-quantitative approach benefits from rigorously tested research technologies (Bryman, 2021; Saunders et al., 2020) and supports statistical analysis and generalisation (Creswell & Creswell, 2020). However, it can

overlook the context or deeper meaning behind the data, which is crucial for understanding complex issues (Bell et al., 2019; Bryman, 2021).

3. **Research approach:** The deductive approach, while suitable for hypothesis testing, may not fully explore emergent themes or unexpected findings that could arise from an inductive approach. This could limit the richness of the data and insights generated (Saunders et al., 2020; Creswell & Creswell, 2020).

4. **Study settings**: The research focuses on the South African mining industry, which may limit the generalisability of the results to other sectors or geographic regions. The unique challenges and dynamics within the mining sector, such as regulatory constraints, technology adoption, culture, and labour relations, may not apply to other sectors (Dayo-Olupona et al., 2023; Wang et al., 2022; Saunders et al., 2020).

5. **Target population:** The target population includes knowledge workers in the South African mining industry, limiting generalisability to other industries or global contexts. Focusing solely on knowledge workers may exclude valuable insights from other roles within the industry (Bryman, 2021). Additionally, voluntary participation in online surveys can introduce self-selection bias, as only motivated individuals may choose to respond (Saunders et al., 2020).

6. **Unit of Analysis**: The study focuses on individual knowledge workers as the unit of analysis, potentially overlooking the influence of team dynamics, organisational culture, and leadership on individual performance and perceptions (Creswell & Creswell, 2020; Kahn, 1990).

7. **Time horizon**: The research utilises a cross-sectional time horizon, gathering data at a point in time, which restricts the research to a short time frame for collecting the survey data. Although cross-sectional studies effectively identify relationships between variables, they do not account for changes over time or causality (Saunders et al., 2020; Bryman, 2021). This limits the ability to track trends or long-term effects of measured constructs.

8. **Sample size and generalisability**: While the sample size calculation considered established guidelines (Hair et al., 2020) and exceeded the minimum requirement for statistical power, it may still not represent the full diversity of knowledge workers in the

mining industry. A larger and more stratified sample could enhance the robustness of the findings (Hair et al., 2021).

9. **Measurement instrument:** The survey questionnaire may still be subject to limitations, despite its validated constructs (Boateng et al., 2018). For instance, reliance on self-reported data can introduce social desirability bias, where respondents may provide answers they perceive as favourable rather than accurate reflections of their experiences (Kock et al., 2021).

10. **Demographic information:** This research focuses solely on knowledge workers in the South African mining industry, with demographic specifics such as age, education, role, and experience limited to the research sample. The number and demographic characteristics of respondents, and the organisations the researcher had access to, may influence the study's findings and limit its generalisability.

11. **Data collection**: Data collection through an online survey may exclude respondents lacking internet access or those less familiar with digital platforms (Couper, 2017). This could lead to a non-representative sample, particularly under-representing knowledge workers in rural or less technologically advanced mining operations.

12. **Data preparation and processing:** While the data preparation involves systematic anonymisation and quality assurance protocols, potential errors in data entry or survey responses may still affect the reliability of the dataset (Field, 2018). Additionally, outliers and missing data points may require careful handling to avoid skewing results, which could limit the robustness of the findings.

13. **Data validity and reliability:** Although the research assesses convergent and discriminant validity, as well as reliability (Hair et al., 2020), limitations persist. Exploratory factor analysis (EFA) may not fully capture the constructs' complexity if items do not load clearly on a single factor. Variations in wording or context during data collection could also impact the reliability of survey items

14. **Data Analysis:** Using SPSS for data analysis allows for robust statistical tests but focuses mainly on surface-level relationships between variables, potentially overlooking deeper complexities. Regression and correlation analyses highlight associations but do not reveal underlying causal mechanisms. Mixed-methods analysis could offer better

insights (Creswell & Creswell, 2020; Hair et al., 2020). Additionally, multicollinearity between variables may distort regression results, necessitating careful analysis.

4.13 Research Methodology Chapter Conclusion

This chapter outlined the research methodology adopted for investigating the relationship between DT, EE, and JP. The study's philosophical foundation is rooted in a positivist paradigm, which guided the use of a deductive research approach. This approach aligns with the study's objective to test pre-determined hypotheses using quantifiable data. The methodological choice, favouring a quantitative design, facilitated the systematic measurement of the constructs under investigation.

The study selected a survey research strategy as the primary research strategy, enabling the collection of comprehensive data within a cross-sectional time horizon. The study defined its setting, target population, and sampling procedures, ensuring a robust sampling process that aimed to balance representativeness and generalisability. With a well-defined unit of analysis focused on individuals within the mining sector, the study provided a specific context for understanding the interplay between DT, EE, and JP.

The study employed reliable and validated measurement instruments for each construct, including bespoke scales for DT, EE, and JP. The study integrated instruments into a survey questionnaire to facilitate efficient data collection. The data preparation process involved rigorous coding and cleaning to ensure the quality of the dataset. The study assessed the instrument's reliability measurement using Cronbach's alpha, with all constructs meeting the threshold for internal consistency. Furthermore, additional statistical methods, such as Pearson's correlation, Exploratory Factor Analysis (EFA), and assumption tests for normality and homoscedasticity, provided further validation and confirmed the robustness of the data. Descriptive statistics offered an overview of the data trends, while it employed inferential analyses, including the Generalised Linear Model (GLM), Spearman's rank correlations, Kendall's Tau correlations, and the Kruskal-Wallis test to test the study's hypotheses rigorously.

Finally, the chapter acknowledged the limitations inherent in the research methodology. These include the cross-sectional time horizon, which restricts causal inferences, and the use of self-reported data, which may introduce biases. Despite these constraints, the methodological design provided a reliable foundation for analysing the complex relationships between DT, EE, and JP, setting the stage for the subsequent discussion and interpretation of results. Therefore, this chapter has demonstrated a clear and rigorous methodology, ensuring the reliability and validity of the study's findings while contributing to the understanding of how DT impacts individual employee JP through EE within the South African mining context.

Chapter 4: Research Methodology					
4.1 Introduction					
4.2 Research Design and Philosophy	4.2.1 Purpose and Philosophy of the Study	4.2.2 Research Approach	4.2.3 Methodological Choice		
4.3 Research Strategy and Time Horizon	4.3.1 Research Strategy	4.3.2 Time Horizon			
4.4 Study Setting and Sample	4.4.1 Study Setting	4.4.2 Target Population	4.4.3 Sample Size	4.4.4 Generalisability	4.4.5 Unit of Analysis
4.5 Measurement Instruments and	4.5.1 Survey Questionnaire	4.5.2 Measuring Instruments	4.5.3 Data Collection		
4.6 Data Preparation	4.6.1 Data Preparation and Coding				
4.7 Reliability Assesment					
4.8 Internal Validity	4.8.1 Confirmatory Factor Analysis	4.8.2 Pearson's Correlation Analysis	4.8.3 Exploratory Factor Analysis (EFA)		
4.9 Assumption Testing	4.9.1 Normality Testing	4.9.2 Homoscedasticity Testing			
4.10 Descriptive Statistics					
4.11 Hypothesis Testing	4.11.1 Generalised Linear Model (GLM	4.11.2 Spearman's Rank and Kendall's Tau Correlations	4.11.3 Kruskal-Wallis Test		
4.12 Research Limitations					
4.13 Conlucion					

Figure 12: Chapter 4 summary structure
Source: Author's illustration

5. Chapter 5: Results

5.1 Introduction

This chapter presents the study's key findings, detailing the relationships and associations between DT, EE and JP, as outlined in the research hypotheses. Using a combination of statistical techniques, including the generalised linear model (GLM), Spearman's Rank, and Kendall's Tau correlations, and the bootstrapping method, the chapter explores the strength and direction of each construct relationship, noting the significant role of EE as a mediating factor. Additionally, the analysis examines demographic factors such as age, education level, job role, and work experience through Kendall's Tau correlations and the Kruskal-Wallis test to understand their influence on DT, EE, and JP. These findings provide a comprehensive view of how DT initiatives and engagement practices impact performance, offering valuable insights for organisations seeking to enhance productivity through targeted digital and engagement strategies. Figure 13 shows the chapter's high-level overview.

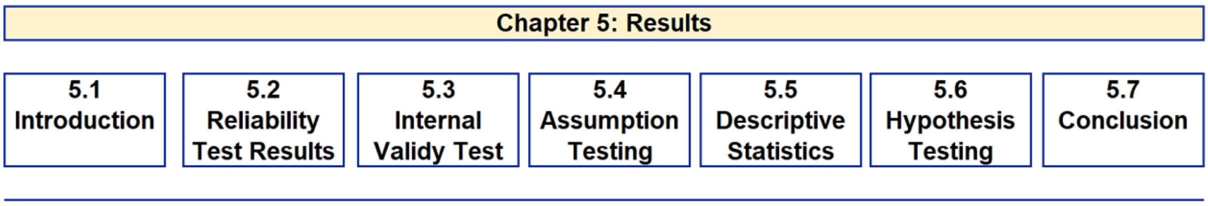

Figure 13: Chapter 5 summary structure
Source: Author's illustration

5.2 Reliability Test Results

After calculating descriptive statistics for the 400 valid responses, the study assessed the reliability of construct measurements using Cronbach's Alpha, as shown in Table 1. Reliability testing ensures the stability and consistency of measurement items, which is a prerequisite for evaluating their validity concerning the intended constructs (Hair et al., 2019). A reliable measurement instrument demonstrates consistency before assessing its accuracy in measuring the construct.

Table 1: Combined Reliability Test Results

Digital Transformation		Employee Engagement		Job Performance	
Cronbach's Alpha	0,886	Cronbach's Alpha	0,949	Cronbach's Alpha	0,950
No. of Items Before Test	5	No. of Items Before Test	12	No. of Items Before Test	13
No. of Items After Test	5	No. of Items After Test	12	No. of Items After Test	13

Source: Author's illustration of results generated by SPSS

The reliability results show strong internal consistency across the three constructs: DT (α = 0.886), EE (α = 0.949), and JP (α = 0.95). Cronbach's Alpha values above 0.7 are considered acceptable, while values exceeding 0.9 indicate excellent reliability. For DT, the Alpha of 0.886 across five items suggests high reliability suitable for exploratory studies. EE, with an Alpha of 0.949 over 12 items, demonstrates very strong consistency, highlighting the meaningful contribution of each item to capturing engagement. Similarly, JP, with an Alpha of 0.95 across 13 items, reflects excellent reliability, capturing the complexity of the construct. Appendix 3 comprises the full reliability test results for each construct.

These Cronbach's Alpha scores confirm the high reliability of the measurement instruments, providing a strong foundation for subsequent statistical analyses. This reliability supports the validity of using these items to explore relationships between DT, EE, and JP, lending credibility to the study's findings.

5.3 Constructs Validity Checks

To further establish the accuracy and relevance of the measurement constructs, the analysis advanced to validity testing through Pearson's bivariate correlation and exploratory factor analysis (EFA). Bivariate correlation provides insights into the strength and direction of relationships between construct items, serving as a preliminary indicator of validity. EFA, as a data reduction technique, explores the latent structure of the constructs, revealing underlying patterns and ensuring that each item aligns well with its intended factor. These steps reinforce the reliability findings by confirming that the constructs accurately represent the concepts being investigated, ultimately supporting a solid foundation for hypothesis testing and inferential analysis.

5.3.1 Pearson's Correlation Test Results

The study performed validity tests for each construct (i.e., DT, EE and JP), using Pearson's correlation method to assess relationships between each construct item and the total construct item. Table 2 split in two halves shows combined high-level internal validity results, which indicate high construct validity measures for the items measuring DT, EE, and JP. Each item within the DT, EE, and JP constructs demonstrates a highly significant positive correlation ($p < 0.05$) with their respective total scores (i.e., DT, EE, JP). For instance, DT items show correlations ranging from 0.748 to 0.880, EE items (EE, EME and BE) range from 0.709 to 0.894, and JP items (TP and CP) range from 0.617 to 0.872. These high correlation coefficients imply that individual items within each construct correlate highly and measure their intended constructs coherently. Appendix 4 shows the full Pearson correlation results for each construct.

Table 2: Person Correlation Results for Internal Validity

		DT		EE		JP			EE		JP
Pearson Correlation	DT1	,822**	CE1	,709**	TP1	,750**	Pearson Correlation	EME3	,775**	CP2	,767**
Sig. (2-tailed)		<0,001		<0,001		<0,001	Sig. (2-tailed)		<0,001		<0,001
N		400		400		400	N		400		400
Pearson Correlation	DT2	,748**	CE2	,814**	TP2	,675**	Pearson Correlation	EME4	,871**	CP3	,872**
Sig. (2-tailed)		<0,001		<0,001		<0,001	Sig. (2-tailed)		<0,001		<0,001
N		400		400		400	N		400		400
Pearson Correlation	DT3	,859**	CE3	,886**	TP3	,782**	Pearson Correlation	BE1	,882**	CP4	,859**
Sig. (2-tailed)		0,000		0,000		0,000	Sig. (2-tailed)		<0,001		<0,001
N		400		400		400	N		400		400
Pearson Correlation	DT4	,839**	CE4	,836**	TP4	,680**	Pearson Correlation	BE2	,894**	CP5	,849**
Sig. (2-tailed)		<0,001		<0,001		<0,001	Sig. (2-tailed)		<0,001		<0,001
N		400		400		400	N		400		400
Pearson Correlation	DT5	,880**	EME1	,756**	TP5	,617**	Pearson Correlation	BE3	,879**	CP6	,844**
Sig. (2-tailed)		<0,001		<0,001		<0,001	Sig. (2-tailed)		<0,001		<0,001
N		400		400		400	N		400		400
Pearson Correlation			EME2	,721**	CP1	,782**	Pearson Correlation	BE4	,855**	CP7	,802**
Sig. (2-tailed)				0,000		0,000	Sig. (2-tailed)		<0,001		<0,001
							N		400		400
							Pearson Correlation			CP8	,774**
							Sig. (2-tailed)				<0,001
							N				400

**. Correlation is significant at the 0.01 level (2-tailed).

Source: Author's illustration of results generated by SPSS

5.3.1.1 Digital Transformation Correlation Results

The correlation matrix in Table 3 for the DT construct reveals that all construct items highly correlate, with values ranging from 0.49 to 0.74, comfortably exceeding the 0.3 threshold. This indicates that all items align strongly with a single factor, making further reduction unnecessary.

Table 3: DT - Pearson Correlation Matrix

DT Correlation Matrix					
	DT1	DT2	DT3	DT4	DT5
DT1	1,00	0,52	0,65	0,60	0,63
DT2	0,52	1,00	0,51	0,49	0,57
DT3	0,65	0,51	1,00	0,67	0,74
DT4	0,60	0,49	0,67	1,00	0,72
DT5	0,63	0,57	0,74	0,72	1,00

Source: Author's own illustration of results generated by SPSS

5.3.1.2 Employee Engagement Correlation Results

The Pearson correlation matrix in Table 4 indicates that all EE construct items highly correlate, with values ranging from 0.41 to 0.81, comfortably exceeding the 0.3 threshold. This indicates that all items align strongly with a single factor, making further reduction unnecessary.

Table 4: EE - Pearson Correlation Matrix

EE - Correlation Matrix												
	CE1	CE2	CE3	CE4	EE1	EE2	EE3	EE4	BE1	BE2	BE3	BE4
CE1	1,00	0,66	0,62	0,60	0,46	0,41	0,45	0,53	0,58	0,57	0,56	0,56
CE2	0,66	1,00	0,81	0,83	0,46	0,44	0,49	0,65	0,70	0,71	0,69	0,64
CE3	0,62	0,81	1,00	0,81	0,58	0,51	0,60	0,75	0,78	0,79	0,80	0,75
CE4	0,60	0,83	0,81	1,00	0,55	0,50	0,51	0,66	0,70	0,72	0,73	0,68
EE1	0,46	0,46	0,58	0,55	1,00	0,71	0,61	0,69	0,61	0,59	0,57	0,58
EE2	0,41	0,44	0,51	0,50	0,71	1,00	0,64	0,63	0,54	0,57	0,53	0,55
EE3	0,45	0,49	0,60	0,51	0,61	0,64	1,00	0,75	0,63	0,66	0,64	0,63
EE4	0,53	0,65	0,75	0,66	0,69	0,63	0,75	1,00	0,76	0,76	0,74	0,68
BE1	0,58	0,70	0,78	0,70	0,61	0,54	0,63	0,76	1,00	0,85	0,81	0,79
BE2	0,57	0,71	0,79	0,72	0,59	0,57	0,66	0,76	0,85	1,00	0,82	0,81
BE3	0,56	0,69	0,80	0,73	0,57	0,53	0,64	0,74	0,81	0,82	1,00	0,84
BE4	0,56	0,64	0,75	0,68	0,58	0,55	0,63	0,68	0,79	0,81	0,84	1,00

Source: Author's own illustration of results generated by SPSS

5.3.1.3 Job Performance Correlation Results

The Pearson correlation matrix Table 5 for the JP construct reveals that all construct items highly correlate, with values ranging from 0.45 to 0.85, comfortably exceeding the 0.3 threshold.

Table 5: JP – EFA Correlation Matrix

JP - Correlation Matrix													
	TP1	TP2	TP3	TP4	TP5	CP1	CP2	CP3	CP4	CP5	CP6	CP7	CP8
TP1	1,00	0,77	0,73	0,64	0,57	0,54	0,62	0,62	0,65	0,66	0,68	0,54	0,59
TP2	0,77	1,00	0,63	0,60	0,55	0,51	0,55	0,54	0,59	0,62	0,60	0,52	0,49
TP3	0,73	0,63	1,00	0,67	0,51	0,61	0,60	0,68	0,68	0,69	0,66	0,60	0,60
TP4	0,64	0,60	0,67	1,00	0,61	0,55	0,49	0,57	0,58	0,61	0,61	0,53	0,52
TP5	0,57	0,55	0,51	0,61	1,00	0,48	0,49	0,50	0,50	0,54	0,54	0,53	0,45
CP1	0,54	0,51	0,61	0,55	0,48	1,00	0,56	0,68	0,60	0,56	0,61	0,56	0,55
CP2	0,62	0,55	0,60	0,49	0,49	0,56	1,00	0,65	0,58	0,59	0,58	0,49	0,53
CP3	0,62	0,54	0,68	0,57	0,50	0,68	0,65	1,00	0,73	0,69	0,69	0,66	0,62
CP4	0,65	0,59	0,68	0,58	0,50	0,60	0,58	0,73	1,00	0,85	0,68	0,62	0,59
CP5	0,66	0,62	0,69	0,61	0,54	0,56	0,59	0,69	0,85	1,00	0,68	0,65	0,57
CP6	0,68	0,60	0,66	0,61	0,54	0,61	0,58	0,69	0,68	0,68	1,00	0,68	0,62
CP7	0,54	0,52	0,60	0,53	0,53	0,56	0,49	0,66	0,62	0,65	0,68	1,00	0,61
CP8	0,59	0,49	0,60	0,52	0,45	0,55	0,53	0,62	0,59	0,57	0,62	0,61	1,00

Source: Author's own illustration of results generated by SPSS

This indicates that all items align strongly with a single factor, making further reduction unnecessary.

5.3.2 Exploratory Factor Analysis (EFA) Results

After confirming construct validity, the study used the EFA variable reduction technique on each construct and its related items, narrowing down the variables for each construct to a more manageable set for inferential statistical analysis. The study conducted an EFA for each construct separately, with the results presented in the following sub-sections.

5.3.2.1 Digital Transformation EFA Results

The DT EFA results in Table 6 indicate a robust factor structure. The KMO value of 0.871, greater than the 0.6 threshold, demonstrates strong sampling adequacy, suggesting the construct items are suitable for aggregating. Bartlett's Test of Sphericity, with a significant Chi-Square (1095.61) and a p-value of ($p < 0.05$), confirms the data's factorability, meaning the variables correlate significantly for factor extraction.

Table 6: DT - KMO and Bartlet's Test and Communalities Results

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0,871
Bartlett's Test of Sphericity	Approx. Chi-Square	1096
	df	10
	Sig.	<0,001

Source: Author's own illustration of results generated by SPSS

The eigenvalues in Table 7 show that the single extracted component with an eigenvalue above 1 accounts for 69.1% of the total variance, which is above the 60% acceptable threshold, further supporting a one-factor solution.

Table 7: DT – Total Variance Results

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	3,456	69,1	69,1	3,46	69,1	69,1
2	0,561	11,2	80,3			
3	0,416	8,3	88,7			
4	0,331	6,6	95,3			
5	0,236	4,7	100,0			

Source: Author's own illustration of results generated by SPSS

The component matrix in Table 8 reveals high loadings (ranging from 0.730 to 0.888) for each DT item, indicating strong correlations with the single extracted component and suggesting all items contribute meaningfully to this underlying factor. Since only one component was extracted and the solution could not be rotated, it implies that the items reflect a unidimensional structure, meaning they measure a single latent construct of DT, which is well-supported by the data.

Table 8: DT Component Matrix and Communalities

Component Matrix		Communalities		
Item Code	Component	Item Code	Initial	Extraction
DT5	0,888	DT1	1,000	0,671
DT3	0,866	DT2	1,000	0,534
DT4	0,843	DT3	1,000	0,750
DT1	0,819	DT4	1,000	0,711
DT2	0,730	DT5	1,000	0,789

Source: Author's own illustration of results generated by SPSS

5.3.2.2 Employee Engagement EFA Results

The EE factor analysis provides several layers of insight through factor extraction and matrix loadings. The high KMO value (0.945) in Table 9 indicates that the variables sufficiently correlate to justify factor analysis, which is reinforced by Bartlett's Test of Sphericity (significant at $p < 0.05$), suggesting significant correlations among variables.

Table 9: EE - KMO and Bartlet's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0,945
Bartlett's Test of Sphericity	Approx. Chi-Square	4749
	df	66
	Sig.	<0,001

Source: Author's own illustration of results generated by SPSS

The total variance in Table 10 shows that the first component accounts for 68.3% of the total variance, suggesting it has the most significant impact on the data, while the second component adds 8.5%, bringing the cumulative explained variance with an eigenvalue above 1 to 76.8%, suggesting that subsequent components may contribute diminishing information.

Therefore, the study reduced the total number of EE components to two, as determined by the cumulative total variance and the eigenvalue.

Table 10: EE Total Variance Results

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8,20	68,34	68,3	8,20	68,3	68,3
2	1,02	8,51	76,8	1,02	8,5	76,8
3	0,61	5,07	81,9			
4	0,44	3,65	85,6			
5	0,39	3,26	88,8			
6	0,32	2,64	91,5			
7	0,25	2,09	93,6			
8	0,19	1,61	95,2			
9	0,16	1,32	96,5			
10	0,15	1,21	97,7			
11	0,14	1,20	98,9			
12	0,13	1,09	100,0			

Source: Author's own illustration of results generated by SPSS

The rotated component matrix in Table 11 shows high loadings across items with distinct separation, showing how each item aligns with specific factors, which aids in clearer interpretation.

Table 11: EE Rotated Component Matrix and Communalities

Rotated Component Matrix			Communalities		
Item Code	Component 1	Component 2	Item Code	Initial	Extraction
CE3	0,884		CE1	1,000	0,556
CE2	0,838	0,385	CE2	1,000	0,822
CE4	0,834	0,301	CE3	1,000	0,850
BE3	0,759	0,475	CE4	1,000	0,786
BE2	0,743	0,514	BE1	1,000	0,797
BE1	0,741	0,498	BE2	1,000	0,816
BE4	0,709		BE3	1,000	0,802
CE1	0,707	0,499	BE4	1,000	0,749
EE2		0,850	EE1	1,000	0,749
EE1	0,307	0,809	EE2	1,000	0,771
EE3	0,364	0,775	EE3	1,000	0,734
EE4	0,570	0,682	EE4	1,000	0,791

Source: Author's illustration of results generated by SPSS

For example, cognitive engagement (CE) and behavioural engagement (BE) items load more distinctly onto component 1, while emotional engagement (EME) items show more shared loadings, indicating potential overlapping themes across components.

5.3.2.3 Job Performance EFA Results

The JP construct EFA results in Table 12 highlight a strong foundation for factor analysis. The Kaiser-Meyer-Olkin (KMO) measure of 0.945 signifies excellent sampling adequacy, meaning the data is suitable for factor analysis, while Bartlett's Test of Sphericity is significant ($p < 0.05$), confirming the presence of sufficient correlations among variables.

Table 12: JP - KMO and Bartlet's Test Results

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0,950
Bartlett's Test of Sphericity	Approx. Chi-Square	4032
	df	78
	Sig.	<0,001

Source: Author's own illustration of results generated by SPSS

The variance and eigenvalues in Table 13 show a dominant first component explaining 63.17% of the variance, underscoring the JP construct's unidimensionality, indicating that a single factor effectively represents the construct. The single extracted component with an eigenvalue above 1 accounting for 63.2% of the total variance, is above the 60% acceptable threshold, further supporting a one-factor solution.

Table 13: JP EFA Results – Total Variance

Total Variance Explained						
	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8,21	63,17	63,2	8,2	63,2	63,2
2	0,764	5,88	69,0			
3	0,600	4,61	73,7			
4	0,563	4,33	78,0			
5	0,497	3,82	81,8			
6	0,467	3,59	85,4			
7	0,408	3,14	88,5			
8	0,345	2,65	91,2			
9	0,301	2,31	93,5			
10	0,271	2,08	95,6			
11	0,250	1,92	97,5			
12	0,190	1,46	99,0			
13	0,134	1,03	100,0			

Source: Author's own illustration of results generated by SPSS

This variance results suggests that the primary factor captures most of the variance, with minimal need for additional components, as seen in the low variance explained by subsequent components.

The component matrix and communalities in Table 14 support the unidimensional structure, with all items loading strongly on the first component, demonstrating that a single cohesive factor can reliably represent the JP construct, reinforcing convergent validity. These findings collectively affirm the construct's robustness and coherence within a single-factor framework.

Table 14: JP Component Matrix and Communalities

Component Matrix		Communalities		
Item Code	**Component**	**Item Code**	**Initial**	**Extraction**
CP5	0,847	TP1	1,000	0,698
TP3	0,843	TP2	1,000	0,595
CP4	0,842	TP3	1,000	0,710
CP6	0,840	TP4	1,000	0,596
CP3	0,839	TP5	1,000	0,488
TP1	0,836	CP1	1,000	0,570
CP7	0,775	CP2	1,000	0,560
TP4	0,772	CP3	1,000	0,705
TP2	0,772	CP4	1,000	0,710
CP1	0,755	CP5	1,000	0,717
CP2	0,748	CP6	1,000	0,705
CP8	0,747	CP7	1,000	0,600
TP5	0,699	CP8	1,000	0,558

Source: Author's own illustration of results generated by SPSS

5.3.3 Revised Construct Components

Table 15 presents the revised construct item labels, with component names aligned with the original constructs; however, the researcher reassigned some items within each component based on the EFA findings.

Based on the EFA results, the DT construct remained unchanged, while the analysis simplified the EE construct from three components: cognitive engagement (CE), behavioural engagement (BE), and emotional engagement (EME) to two components: cognitive and behavioural Engagement (CBE) and emotional engagement (EME). Additionally, the analysis reduced the JP construct from task performance (TP) and contextual performance (CP) to a single component that combines task and contextual performance items.

Table 15: Revised Construct Items and Labels based on EFA

Construct Name	Previous Components	Previous Items	New Components	New Items
Digital Tranformation - DT	Digital Tranformation - DT	DT1 - DT5	Digital Tranformation - DT	DT1 - DT5
Employee Engagement - EE	Cognitive Engagement - CE	CE1 - CE4	Cognitive and Behavioural Engagement - CBE	CE1 - CE4 BE1 - BE4
	Behavioural Engagement - BE	BE1 - BE4		
	Emotional Engagement - EME	EME1 - EME4	Emotional Engagement - EME	EME1 - EME4
Job Performance - JP	Task Performance - TP	TP1 - TP8	Job Performance - JP	TP1 - TP8 CP1 - CP8
	Contextual Performance - CP	CP1 - CP8		

Source: Author's own illustration of results generated by SPSS

Figure 14 illustrates the revised conceptual model based on the EFA outcomes, including the hypotheses related to these constructs and their components to enable hypothesis testing at both construct and sub-construct (or component) levels. Sub-construct or component-level hypotheses have subscripts "a" and "b". The average score for all items comprising a construct or sub-construct calculates the total construct or sub-construct scores. The researcher used these computed constructs and sub-construct scores for further analysis, including assessments of normality, homoscedasticity, and hypothesis testing.

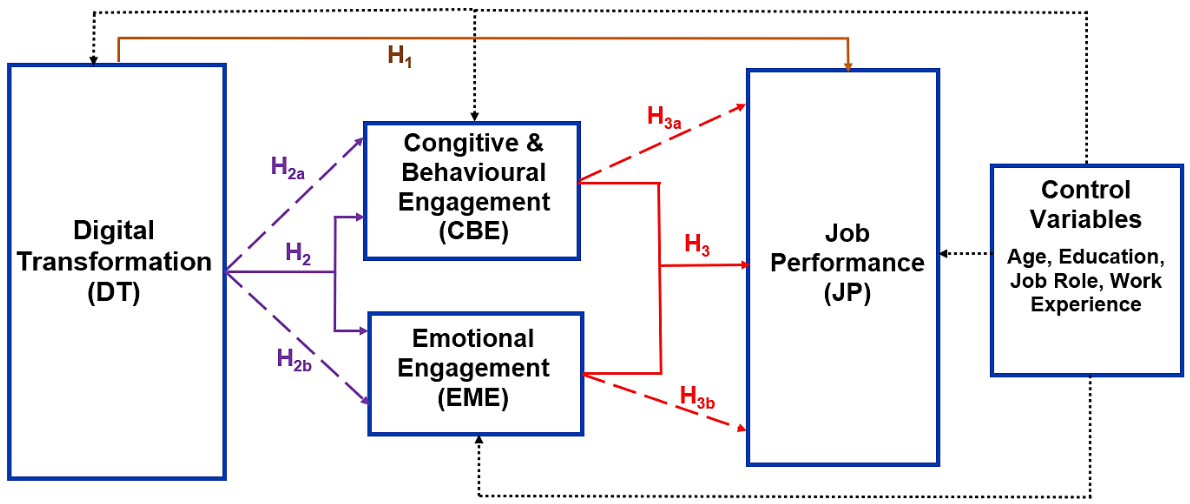

Figure 14: The Revised and Detailed Conceptual Model for Hypotheses Testing
Source: Author's illustration of results generated by SPSS

5.4 Assumptions Testing

Following the EFA, assumption testing is essential to prepare the data for further statistical procedures, with recent research underscoring its importance in ensuring reliable results (Pallant, 2020; Tabachnick & Fidell, 2019). This section addresses critical assumptions, including normality and homoscedasticity, both integral to the accuracy of inferential statistics (Hair et al., 2019). Normality tests assess whether data distribution follows a normal curve, a condition that influences statistical power and validity (Boateng et al., 2018). On the other hand, homoscedasticity tests evaluate the consistency of variances across variables, ensuring that results remain unbiased and interpretations are robust (Cohen et al., 2013). Verifying these assumptions strengthens the foundation for dependable and meaningful subsequent analyses.

5.4.1 Normality Test Results

The normality test graphs for the DT construct, the cognitive behavioural engagement (CBE) and emotional engagement (EME) sub-constructs, and the Job JP construct, indicate that the data does not follow a perfectly normal distribution. The Q-Q plots in Figures 15, 16, 17 and 18 for each construct show data points deviating from the diagonal line, especially in the upper and lower quantiles, suggesting skewness in the distribution. This departure from the line indicates a non-symmetrical alignment of the data points with the expected quantiles of a normal distribution.

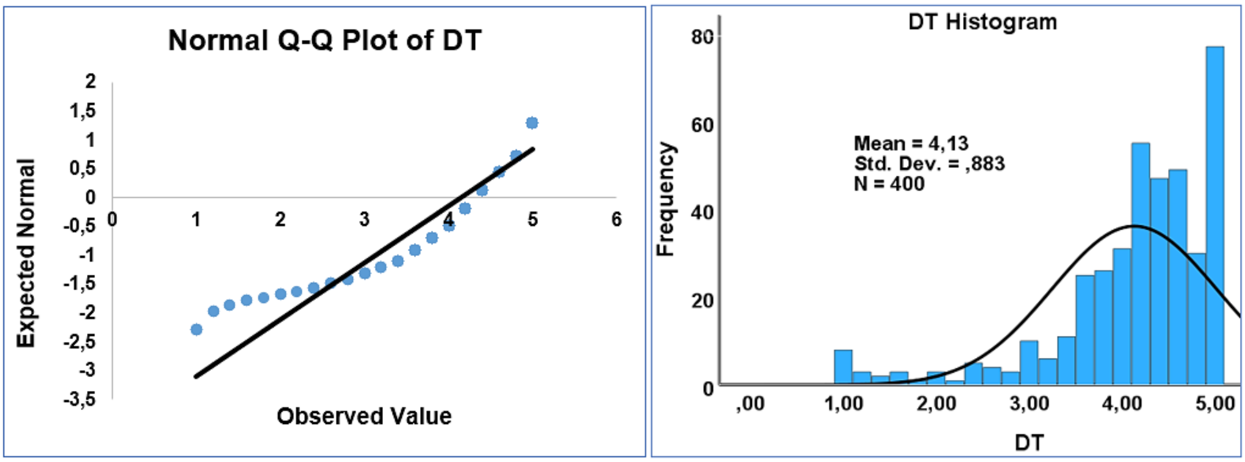

Figure 15: DT Q-Q and Histogram Plots
Source: Author's illustration of results generated by SPSS

The histogram graphs in Figures 15, 16, 17 and 18 further confirm this, showing right-hand side distributed data with negatively skewed tails for all constructs. These rightward-distributed results imply that higher values are more frequent, with a longer negatively skewed tail extending towards the lower end of the scale. The positively distributed data with negatively skewed tails on both the Q-Q plots and histograms suggest that most respondents provided higher ratings. This large negative skewness suggests that the assumptions of normality may not hold, which is important to consider when selecting further parametric or non-parametric analyses.

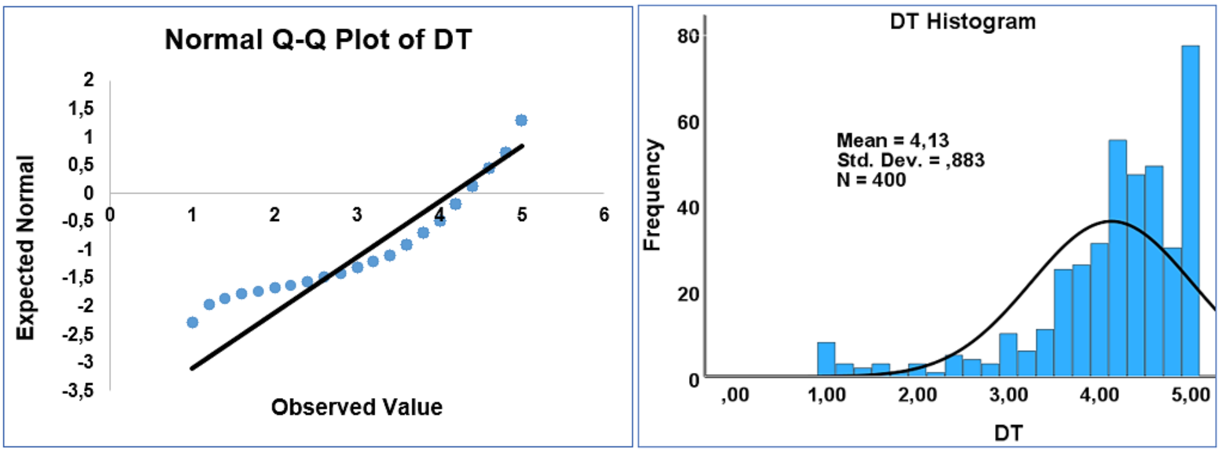

Figure 16: EME Q-Q and Histogram Plots
Source: Author's illustration of results generated by SPSS

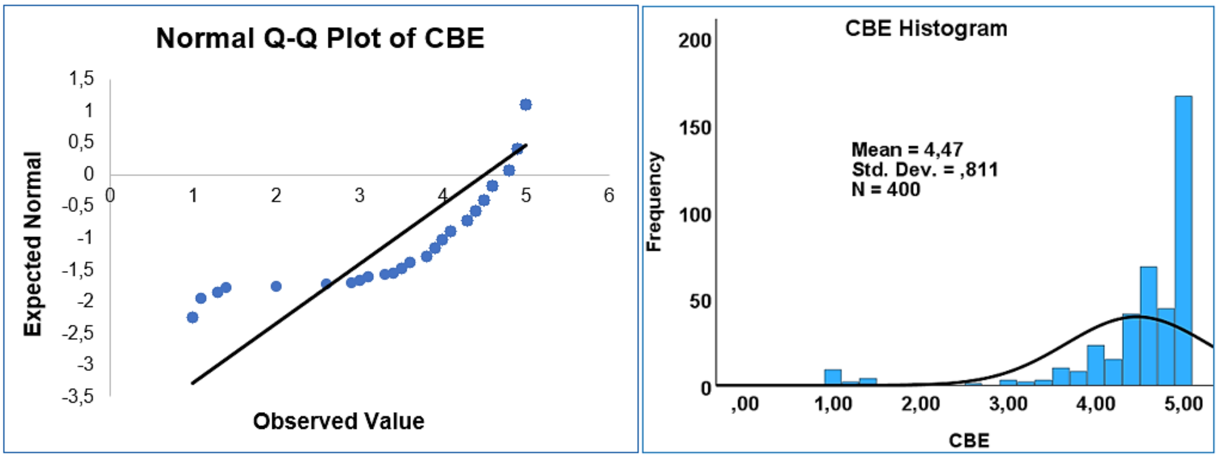

Figure 17: CBE Q-Q and Histogram Plots
Source: Author's illustration of results generated by SPSS

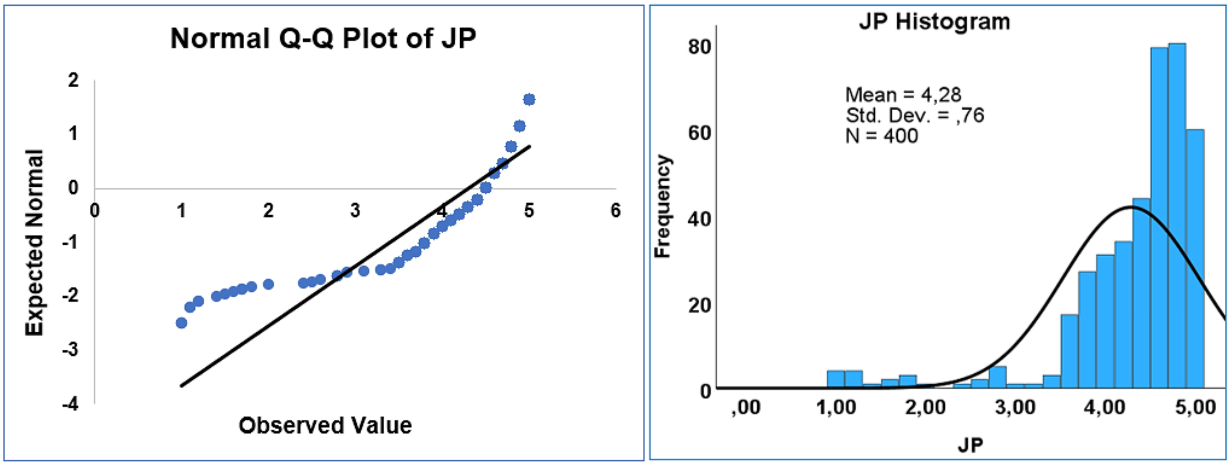

Figure 18: EME Q-Q and Histogram Plots
Source: Author's illustration of results generated by SPSS

The descriptive statistics in Table 16, showing notably high negative skewness and positive kurtosis values, reinforce the indications of non-normality for the data. These statistics suggest right-distributed data with pronounced peaks, implying that data points cluster more around certain values than would be expected in a normal distribution.

Table 16: Data Descriptive Statistics for Normality Test

Descriptive Statistics							
Construct Components	N	Mean	Std. Deviation	Skewness		Kurtosis	
				Statistic	Std. Error	Statistic	Std. Error
DT	400	4,13	0,883	-1,71	0,122	3,18	0,243
EME	400	4,29	0,874	-1,71	0,122	2,86	0,243
CBE	400	4,47	0,811	-2,88	0,122	9,04	0,243
JP	400	4,28	0,760	-2,37	0,122	6,70	0,243

Source: Author's illustration of results generated by SPSS

The Kolmogorov-Smirnov and Shapiro-Wilk normality tests in Table 17 yield p-values well below 0.05, confirming a significant non-normal distribution across all constructs. Standard deviations ranging from 0.760 to 0.883 suggest consistent responses, with lower values indicating uniformity and higher values showing varied opinions. Negative skewness across datasets points to a tendency towards higher scores, reflecting an overall positive outlook among participants. Kurtosis values vary, with some items, like CBE (9.04), indicating a sharp peak and others more moderate, showing diverse response patterns around the mean. These insights confirm a non-normal data distribution, emphasising the need for careful selection of analytical methods. Overall, the results indicate a shared positive perspective, though with some variability in enthusiasm across measures, as evidenced by mean scores and standard deviations, setting the stage for further analysis.

Table 17: Kolmogorov-Smirnov and Shapiro-Wilk Normality Test Results

Tests of Normality

Construct Components	Kolmogorov-Smirnov			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
DT	0,177	400	<0,001	0,821	400	<0,001
EME	0,209	400	<0,001	0,786	400	<0,001
CBE	0,256	400	<0,001	0,634	400	<0,001
JP	0,173	400	<0,001	0,750	400	<0,001

Source: Author's illustration of results generated by SPSS

5.4.2 Homoscedasticity Test Results

The homoscedasticity test results in Figure 19 revealed distinct non-random patterns, particularly noticeable within the ranges of -5 to -2 and -1 to 1 on the spectrum of standardised residuals. The highlighted section shows the predicted values. These areas of concentrated, non-random variance suggest heteroscedasticity, meaning that the data variability is inconsistent across the spectrum.

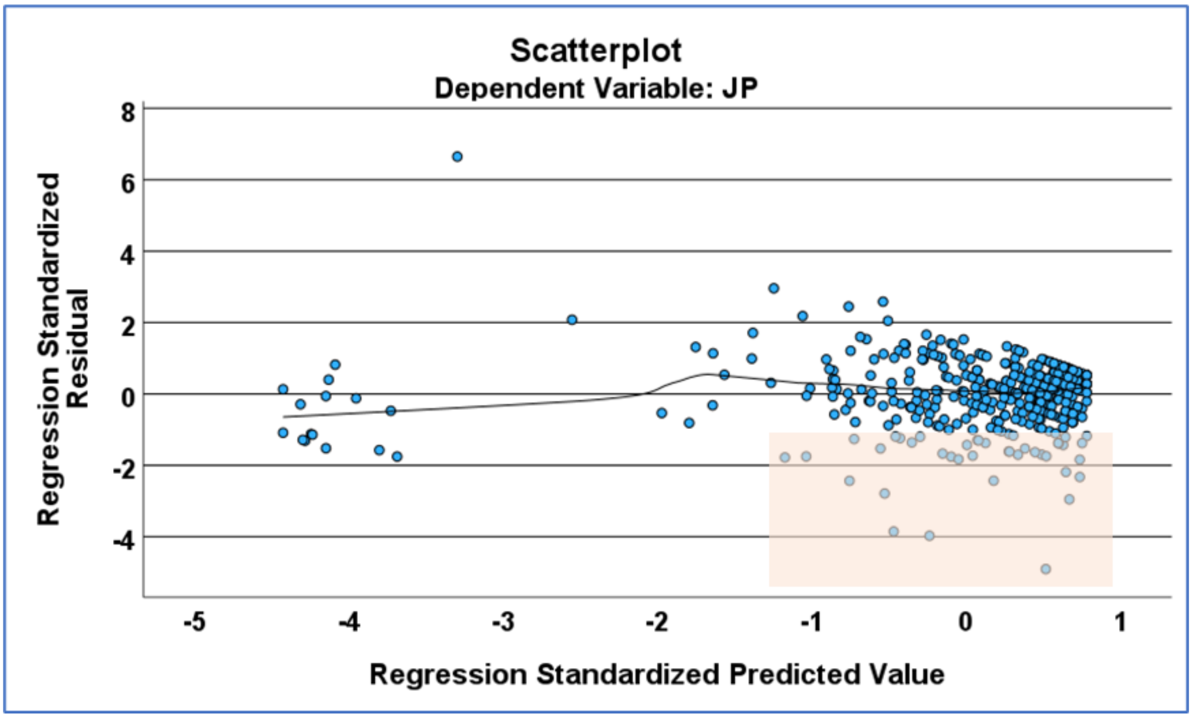

Figure 19: Homoscedasticity Test Outcomes for the Dependant Variable
Source: Author's illustration of results generated by SPSS

The modified Breusch-Pagan and White tests in Table 18 confirm the presence of heteroscedasticity in the dataset, as evidenced by significant Chi-square statistics (Breusch-Pagan: χ^2 = 16.192, p <0.05; White: χ^2 = 48.350, p <0.05). These results reject the null hypothesis, which assumes that the variance of the error terms is constant across levels of the independent variables (DT, CBE, and EME).

The Breusch-Pagan test detects linear relationships between the error variance and independent variables, while the White test goes further by examining non-linear relationships and interaction terms. The significant results from both tests suggest that the error variance changes as a function of these predictors, indicating non-constant variance, or heteroscedasticity, in the model.

Table 18: Modified Breusch-Pagan and White Test Results

Modified Breusch-Pagan Test for Heteroskedasticity			White Test for Heteroskedasticity		
Chi-Square	df	Sig.	Chi-Square	df	Sig.
16,192	1	<0,001	48,350	9	<0,001
a. Dependent variable: JP			a. Dependent variable: JP		
b. Tests the null hypothesis that the variance of the errors does not depend on the values of the independent variables.			b. Tests the null hypothesis that the variance of the errors does not depend on the values of the independent variables.		
c. Predicted values from design: Intercept + DT + CBE + EME			c. Design: Intercept + DT + CBE + EME + DT * DT + DT * CBE + DT * EME + CBE * CBE + CBE * EME + EME * EME		

Source: Author's illustration of results generated by SPSS

In practical terms, this inconsistency can impact the reliability of regression coefficients and associated statistical significance tests, as homoscedasticity is a key assumption in linear regression models. This pattern implies that residuals, rather than being evenly spread around the predicted values, cluster in certain ranges, indicating that variance may differ across different levels of the independent variable. Consequently, these results advise caution, as violating the homoscedasticity assumption can potentially distort interpretations, leading to biased estimates and unreliable inferential conclusions.

5.5 Descriptive Statistics

After defining the study's hypotheses, the study conducted a descriptive statistical analysis to examine patterns and trends within the data and to evaluate initial relationships among the variables relevant to each hypothesis. This approach provided a foundational understanding of the sample characteristics and distribution patterns across constructs and sub-constructs like DT, CBE, EME, and JP. Descriptive statistics, such as mean, median, and mode scores and frequency distributions allowed for construct items' comparisons to assess initial variances in DT, CBE, EME, and JP. Furthermore, the study identified key demographic variables, including age, education level, job role, and work experience, as potentially influential factors in these constructs before proceeding to more complex inferential testing. This preliminary analysis established a clear context for understanding how the sample's characteristics might impact the study's main constructs, informing the subsequent hypothesis testing steps.

5.5.1 Constructs Data Descriptive Statistics

5.5.1.1 High-Level Data

The descriptive statistics for the constructs presented in Table 19 show a generally high level of agreement among respondents across all items. The DT construct has a mean of 4.13, with a median of 4.40 and a mode of 5.00, indicating moderate agreement and a relatively low standard deviation of 0.883, suggesting consistency in responses. The EE construct has the highest mean of 4.40, with a median of 4.70 and a mode of 4.80, reflecting strong agreement and a low standard deviation of 0.783, indicating a minimal variation in responses. CBE has a mean of 4.47, with a median of 4.80 and a mode of 5.00, suggesting high agreement and a standard deviation of 0.811, showing some variation, but still consistent. EME has a mean of 4.29, with a median of 4.50 and a mode of 5.00, indicating a slightly lower level of agreement compared to CBE, with a standard deviation of 0.874, reflecting a moderate spread in responses. Finally, JP has a mean of 4.28, with a median of 4.50 and a mode of 4.80, showing high agreement and a standard deviation of 0.760, indicating a relatively consistent response pattern.

Table 19: High-Level Descriptive Statistics for Constructs and Sub-Constructs

Descriptive Statistics					
Construct	**Mean**	**Median**	**Mode**	**Std. Deviation**	**N**
DT	4,13	4,40	5,00	0,883	400
EE	4,40	4,70	4,80	0,783	400
CBE	4,47	4,80	5,00	0,811	400
EME	4,29	4,50	5,00	0,874	400
JP	4,28	4,50	4,80	0,760	400

Source: Author's illustration of results generated by SPSS

Among these constructs, CBE stands out as a significant contributor to its overall EE construct score which has a mean of 4.40, given its high mean and consistent responses.

DT has the lowest average score of 4.13 followed by JP with an average score of 4.28. However, all these constructs reflect strong agreement and low variation.

5.5.1.2 Digital Transformation Construct

The descriptive statistics for the DT construct items in Table 20 reveal varying levels of agreement and response distributions. Item DT2, which focuses on the organisation's efforts to collect large amounts of data from different sources, received the highest mean score of 4.25, indicating strong agreement among respondents, with little variation (STD = 1.076). Similarly, DT5, concerning the organisation's aim to achieve information exchange through digitalisation, also scored highly with a mean of 4.23 and minimal variation (STD = 1.039), suggesting it significantly contributes to the overall DT construct score. DT1, related to the goal of digitalising everything that can be digitalised, had a mean of 4.08, showing a moderate level of agreement, while DT3, about increasing connectivity between business processes, scored a mean of 4.12, with both items reflecting a slightly broader distribution of responses (STDs of 1.081 and 1.058, respectively). Lastly, DT4, which focuses on enhancing the customer interface through digitalisation, scored the lowest mean of 3.97, indicating somewhat less agreement and a higher spread in responses (STD = 1.069). Overall, DT2 and DT5 emerge as the most significant contributors to the construct score, reflecting the high value placed on data collection and information exchange in driving DT within the organisation.

Table 20: Descriptive Statistics for the DT Construct

Descriptive Statistics - DT Construct						
Item Code	**Construct Item Statement**	**Mean**	**Median**	**Mode**	**Std. Deviation**	**N**
DT1	In my organisation, we aim to digitalise everything that can be digitalised.	4,08	4,00	5,00	1,081	400
DT2	In my organisation, we collect large amounts of data from different sources.	4,25	5,00	5,00	1,076	400
DT3	In my organisation, we aim to increase connectivity between different business processes through digitisation.	4,12	4,00	5,00	1,058	400
DT4	In my organisation, we aim to enhance customer interface through digitalisation.	3,97	4,00	5,00	1,069	400
DT5	In my organisation, we aim to achieve information exchange through digitalisation.	4,23	5,00	5,00	1,039	400

Source: Author's illustration of results generated by SPSS

5.5.1.3 Employee Engagement Construct

The descriptive statistics for the items under cognitive engagement (CE) and behavioural engagement (BE) grouped as CBE in Table 21 show generally high levels of agreement among respondents. For CE items, CE3 ("I give my job responsibility a lot of attention") has the highest mean of 4.63, with a median and mode of 5.00, reflecting strong agreement and minimal variation (STD = 0.874). CE2 ("I concentrate on my job when I am at work") follows closely with a mean of 4.45, and both the median and mode are 5.00, indicating a high level of consistency in responses (STD = 0.946). CE4 ("At work, I am focused on my job") also shows strong agreement with a mean of 4.48, while CE1 ("I am really too focused when I am working") has the lowest mean of 4.13, but still shows significant agreement, with a median of 4.00 and a mode of 5.00, and a higher standard deviation of 1.018, suggesting more variation in responses.

Table 21: Descriptive Statistics for the CBE Sub-Construct

Descriptive Statistics - CBE Sub-Construct						
Item Code	**Construct Item Statement**	**Mean**	**Median**	**Mode**	**Std. Deviation**	**N**
CE1	I am really too focused when I am working.	4,13	4,00	5,00	1,018	400
CE2	I concentrate on my job when I am at work.	4,45	5,00	5,00	0,946	400
CE3	I give my job responsibility a lot of attention.	4,63	5,00	5,00	0,874	400
CE4	At work, I am focused on my job.	4,48	5,00	5,00	0,931	400
BE1	I really push myself to work beyond what is expected of me.	4,46	5,00	5,00	0,946	400
BE2	I am willing to put in extra effort without being asked.	4,56	5,00	5,00	0,927	400
BE3	I often go above what is expected of me to help my team be successful.	4,56	5,00	5,00	0,885	400
BE4	I work harder that expected to help my company be successful.	4,39	5,00	5,00	0,943	400

Source: Author's illustration of results generated by SPSS

For BE items, BE2 ("I am willing to put in extra effort without being asked") and BE3 ("I often go above what is expected of me to help my team be successful") have the highest means of 4.56, with medians and modes of 5.00, indicating a high level of agreement and minimal variation (STDs of 0.927 and 0.885, respectively). BE1 ("I really push myself to work beyond what is expected of me") has a mean of 4.46, also reflecting high agreement, with a median and mode of 5.00 and a standard deviation of 0.946. BE4 ("I work harder than expected to help my company be successful") has the lowest mean of 4.39, but still shows high agreement with a median and mode of 5.00 and a standard deviation of 0.943.

Overall, CE3, BE2, and BE3 stand out as significant contributors to their respective construct scores due to their high means and consistent responses, reflecting strong engagement in cognitive and behavioural aspects of work.

The descriptive statistics for the emotional engagement EME items in Table 22 indicate a generally high level of agreement, though with some variation in responses. EME4 ("I care about the future of my company") has the highest mean of 4.55, with a median and mode of 5.00, suggesting strong emotional engagement with minimal variation (STD = 0.938).

EME3 ("I believe in the mission and purpose of my company") also shows strong agreement, with a mean of 4.31, a median of 5.00, and a mode of 5.00, indicating high emotional connection to the company's purpose and mission (STD = 1.027). EME1 ("Working at my current organisation has a great deal of personal meaning to me") has a mean of 4.24, indicating a strong emotional connection, though with slightly more variation (STD = 0.999). EME2 ("I feel a strong sense of belonging to my job") has the lowest mean of 4.01, suggesting a somewhat weaker emotional connection, with a median of 4.00 and a mode of 5.00, and a higher standard deviation of 1.078, reflecting more diversity in responses.

Table 22: Descriptive Statistics for the EME Sub-Construct

Descriptive Statistics - EME Sub-Construct						
Item Code	**Construct Item Statement**	**Mean**	**Median**	**Mode**	**Std. Deviation**	**N**
EME1	Working at my current organisation has a great deal of personal meaning to me.	4,24	5,00	5,00	0,999	400
EME2	I feel a strong sense of belonging to my job.	4,01	4,00	5,00	1,078	400
EME3	I believe in the mission and purpose of my company.	4,31	5,00	5,00	1,027	400
EME4	I care about the future of my company.	4,55	5,00	5,00	0,938	400

Source: Author's illustration of results generated by SPSS

Overall, EME4 and EME3 appear to have the highest contribution to the construct score because of their higher means and consistent responses, highlighting strong emotional engagement with the company's future and mission.

5.5.1.4 Job Performance Construct

The descriptive statistics for the task performance (TP) and contextual performance (CP) items in Table 23 suggest relatively high levels of agreement among respondents, with some variation in responses.

For task performance (TP), the item with the highest mean is TP3 ("I keep in mind the results that I have to achieve in my work") with a mean of 4.52, indicating a strong focus on results. TP1 ("I manage to plan my work so that it is done on time") follows this closely with a mean of 4.36, suggesting strong time management skills. TP4 ("I am able to separate main issues from side issues at work") has a mean of 4.31, reflecting the ability to prioritise tasks effectively, while TP2 ("My planning is optimal") and TP5 ("I am able to perform my work well with minimal time and effort") have slightly lower means (3.98 and 3.89, respectively), indicating moderate levels of agreement and slightly more variation in responses.

For contextual performance (CP), the items show similarly high mean scores. CP3 ("I take on challenging work tasks, when available") and CP4 ("I work at keeping my job knowledge up-to-date") both have means of 4.43 and 4.38, respectively, suggesting that employees actively seek out challenges and prioritise keeping their knowledge current. CP6 ("I come up with creative solutions to new problems") and CP8 ("I actively participate in work meetings") also show high means (4.35 and 4.36), indicating active engagement in problem-solving and meetings. Items such as CP1 ("I take on extra responsibilities") and CP2 ("I start new tasks myself, when my old ones are finished") have slightly lower means (4.23 and 4.29), though they still indicate a high level of engagement with responsibilities and initiative. CP7 ("I keep looking for new challenges in my job") has the lowest mean at 4.25, suggesting slightly less agreement with seeking new challenges, though it still indicates a strong focus on career development.

Table 23: Descriptive Statistics for the JP Construct

Descriptive Statistics - JP Construct						
Item Code	**Construct Item Statement**	**Mean**	**Median**	**Mode**	**Std. Deviation**	**N**
TP1	I manage to plan my work so that it is done on time.	4,36	5,00	5,00	0,947	400
TP2	My planning is optimal.	3,98	4,00	4,00	1,006	400
TP3	I keep in mind the results that I have to achieve in my work.	4,52	5,00	5,00	0,898	400
TP4	I am able to separate main issues from side issues at work.	4,31	5,00	5,00	0,952	400
TP5	I am able to perform my work well with minimal time and effort.	3,89	4,00	4,00	1,094	400
CP1	I take on extra responsibilities.	4,23	5,00	5,00	1,008	400
CP2	I start new tasks myself, when my old ones are finished.	4,29	5,00	5,00	1,056	400
CP3	I take on challenging work tasks, when available.	4,43	5,00	5,00	0,912	400
CP4	I work at keeping my job knowledge up-to-date.	4,38	5,00	5,00	0,929	400
CP5	I work at keeping my job skills up-to-date.	4,38	5,00	5,00	0,916	400
CP6	I come up with creative solutions to new problems.	4,35	5,00	5,00	0,908	400
CP7	I keep looking for new challenges in my job.	4,25	4,00	5,00	0,948	400
CP8	I to actively participate in work meetings.	4,36	5,00	5,00	0,953	400

Source: Author's illustration of results generated by SPSS

Items that contribute significantly to the construct scores include TP3, CP3, CP4, and CP6, as they show higher means and relatively low standard deviations, indicating strong and consistent responses across the sample. These items reflect an individual's performance in both task-specific and contextual performance contexts.

5.5.2 Demographics Data Descriptive Statistic

The descriptive statistics of demographic information provide foundational insights into the sample population's characteristics. The data covers chronological age, educational attainment, professional roles, and work experience, all of which provide a valuable context for understanding how these characteristics relate to DT, CBE, EME, and JP. These variables offer an overview of demographic diversity within the sample, indicating its potential influence on engagement and adaptability to new technologies in the workplace.

5.5.3 Age Distribution

Figure 20 depicts that the age distribution shows that the majority of respondents fall within the 30-39 age group (39%), followed by the 40-49 age group (32%). The 18-29 age group comprises 10%, while the 50-59 group accounts for 16%. Notably, only 3% of respondents are over 60 years old. This suggests a sample composition with a predominantly middle-aged workforce, suggesting that the respondents may have significant work experience and career stability.

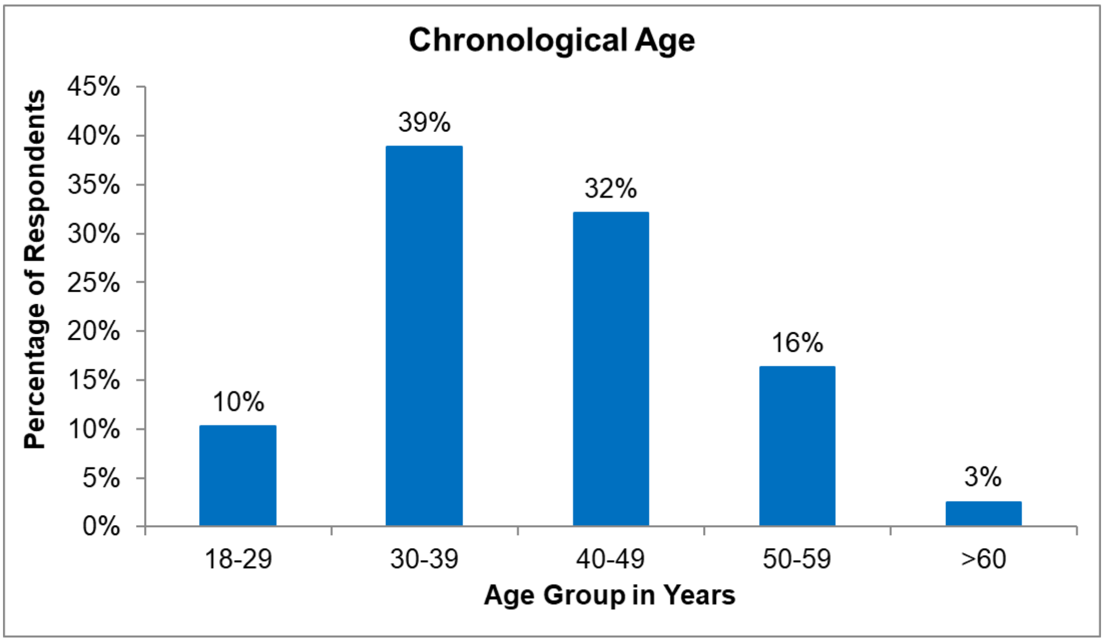

Figure 20: Chronological age demographic
Source: Author's illustration of results generated by SPSS

5.5.4 Educational Level

Figure 21 depicts that most participants hold advanced degrees, with 41% possessing postgraduate qualifications, 29% holding bachelor's degrees, 22% holding diplomas and only 9% having matric qualifications. This distribution suggests a well-educated respondent pool, with a majority holding advanced degrees, followed by a considerable number achieving higher education levels, which may correlate with their professional roles. The educational qualifications of the respondents indicate a fairly knowledgeable workforce.

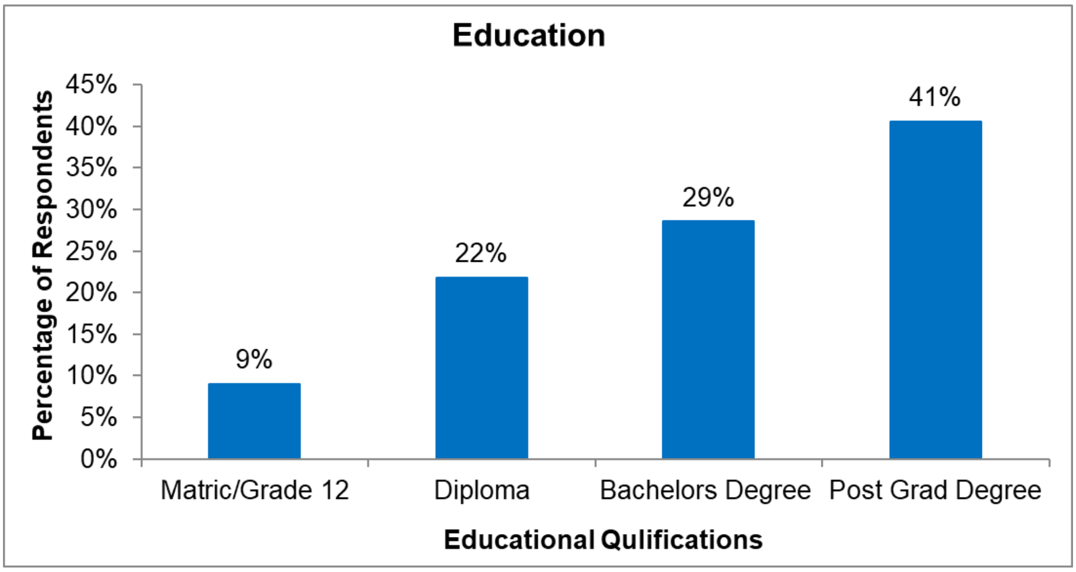

Figure 21: Educational level demographic
Source: Author's illustration of results generated by SPSS

5.5.5 Job Roles

Figure 22 shows that most participants are specialists (36%), indicating that many respondents are likely to be in technical or specialised positions. Managers comprise 27%, while a smaller group is in senior management roles (11%) and a few executives (5%). The prominence of mid-level professionals suggests that the data reflects the experiences of those directly involved in operational aspects of digital change, with some influence from higher-level decision-makers. This distribution suggests a hierarchical structure within the workforce, with a strong emphasis on specialised roles, which may reflect the nature of the industry represented by the respondents. Understanding their perspective is essential for analysing the impact of DT on both operational and managerial performance.

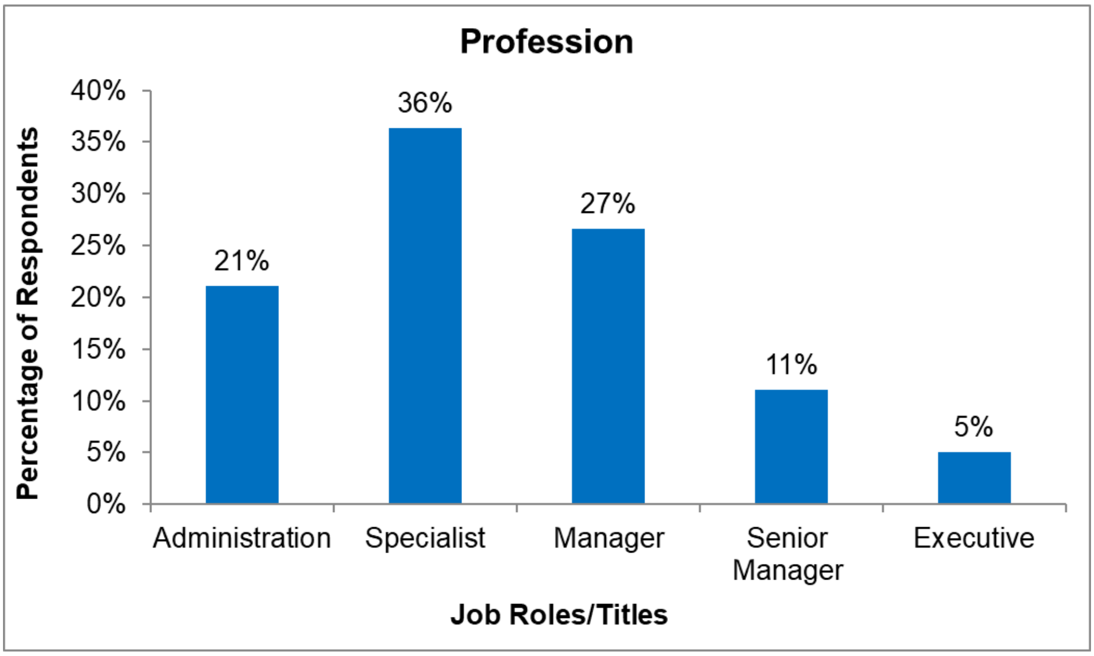

Figure 22: Profession or job roles demographic
Source: Author's illustration of results generated by SPSS

5.5.6 Work Experience

Figure 23 depicts that the majority of respondents have 1-5 years of experience in their current roles (48%), indicating many participants are relatively new in their positions. Meanwhile, 16% have 6-10 years, and only 7% have over 20 years of experience.

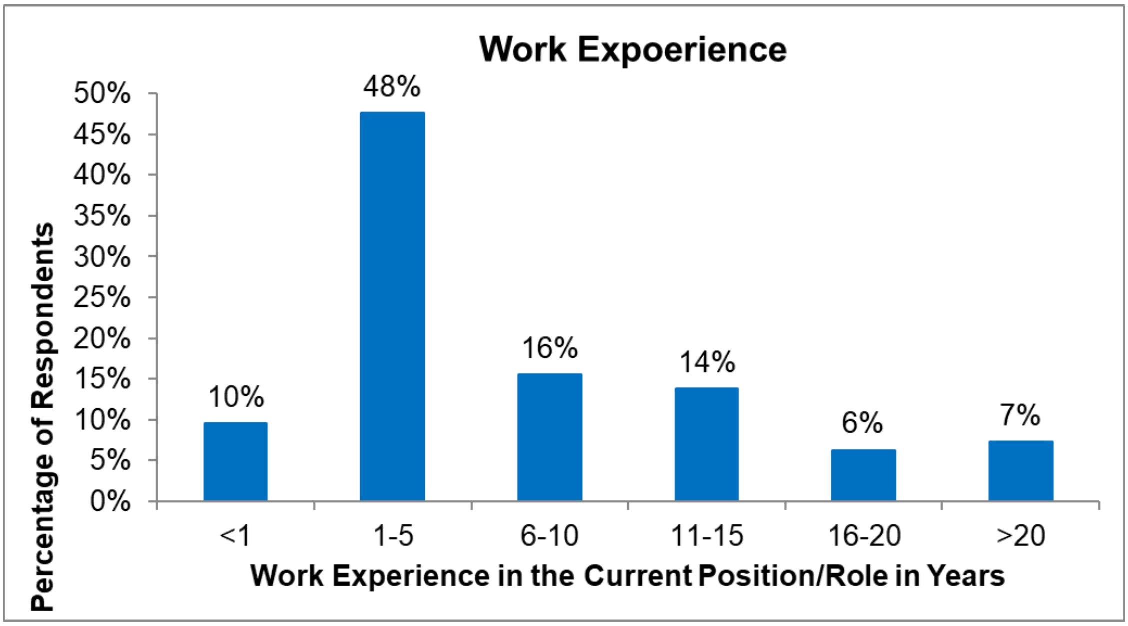

Figure 23: Work experience demographic
Source: Author's illustration of results generated by SPSS

The concentration of respondents in the earlier stages of their roles may reflect a dynamic work environment where employees are either frequently transitioning into new roles or an industry that is experiencing growth and hiring new talent. This relatively new workforce could still be adjusting to digital technologies offered by their new organisations, which is relevant when analysing their engagement and JP amidst ongoing DT efforts (Shuck et al., 2017; Ye et al., 2024).

5.6 Hypotheses Testing

This study employed a full factorial generalised linear model (GLM) and non-parametric statistical analyses, specifically Spearman's rank and Kendall's Tau correlations, to rigorously examine the relationships within the dataset. The presence of non-normality and heteroscedasticity in the data supports the model selection, as GLMs can accommodate varying variances and are less influenced by outliers, thereby enhancing the robustness of the analyses (Hair et al., 2020; Tabachnick & Fidell, 2019). Furthermore, non-parametric methods like Kendall's Tau and Spearman's rank correlations provide valid measures of association that do not rely on the assumptions of normality or homoscedasticity, thus offering greater robustness in the findings (Pallant, 2020; Ye et al., 2024). In addition, the study employed the bootstrapping method in a linear regression model to assess EE direct mediating effect on the DT-JP relationship. Integrating these methodologies provided a comprehensive evaluation of the underlying patterns in the data while accounting for potential violations of standard statistical assumptions, thereby strengthening the validity of the findings.

Furthermore, the study employed the Kruskal-Wallis test to assess whether differences in age group, educational level, job roles, and work experience significantly impacted DT, contextual behavioural engagement (CBE), emotional engagement (EME), and JP. This non-parametric test is particularly suitable for non-normally distributed data with heteroscedasticity, as it does not assume equal variances across groups (Pallant, 2020; Hair et al., 2020). The Kruskal-Wallis test is particularly suited for this analysis due to its ability to handle non-normally distributed data and conditions of heteroscedasticity, making it a robust alternative to parametric tests like ANOVA (Field, 2022; Hair et al., 2021). Recent literature underscores the effectiveness of the Kruskal-Wallis test in various fields, demonstrating its utility for analysing ordinal and continuous data that violate normality assumptions (Pallant, 2020). By utilising the Kruskal-Wallis test, the study effectively analysed differences in the demographic data, providing robust insights into how demographic factors influence these constructs (Hair et al., 2021). The application of this method ensures that the results reflect genuine patterns rather than artefacts of data distribution, thereby strengthening the study's conclusions.

5.6.1 Study Hypotheses

After completing the EFA and the subsequent grouping of construct components, the study formulated specific hypotheses based on the refined model outlined in Section 5.3.3. The EFA process identified key components within each construct, allowing for a more precise representation of the underlying factors. The refined model informed the development of hypotheses in Table 24, that address the relationships and potential interactions between the constructs of interest. The study tests these constructs' structural validity and predictive capacity within the proposed framework by aligning the hypotheses with the newly grouped factors. These hypotheses provide a foundation for examining how the constructs relate to each other and contribute to the overall model, ensuring close ties between theoretical implications and empirical findings derived from the factor analysis.

Table 24: Study Hypotheses

Hypothesis	Relationship in The Model	Hypothesis Type	Hypothesis Test Method
H1	DT has a positive association with JP	Relational	Kendall's Tau
H2	DT has a positive association with EE	Relational	Kendall's Tau
H2a	DT has a positive association with CBE	Relational	Kendall's Tau
H2b	DT has a positive association with EME	Relational	Kendall's Tau
H3	EE has a positive association with JP	Relational	Kendall's Tau
H3a	CBE has a positive association with JP	Relational	Kendall's Tau
H3b	EME has a positive association with JP	Relational	Kendall's Tau

Source: Author's illustration of results generated by SPSS

5.6.2 Inferential Hypotheses Testing

This study utilised a comprehensive factorial generalised linear model (GLM) alongside non-parametric statistical tests, including Spearman's rank and Kendall's Tau correlations, to thoroughly investigate the relationships across the dataset.

5.6.2.1 Generalised Linear Model (GLM)

The results from the full factorial generalised linear model in Table 25 demonstrate that DT, CBE, and EME significantly influence JP, accounting for 71% of its variability (R-squared = 0.710). This high level of explanatory power underscores the importance of these predictors for JP, with CBE emerging as the most influential predictor, as reflected by its large F-value (205.9, $p < 0.05$) and partial eta squared of 0.342. This suggests CBE accounts for a substantial portion of JP variance, highlighting its critical role. EME and DT also significantly impact JP but with more moderate effect sizes, reflected in their partial eta squared values of 0.036 and 0.025, respectively, indicating a lower yet meaningful influence.

Furthermore, the model's intercept is also significant ($F = 25.6$, $p < 0.05$), establishing a baseline for JP in the absence of other variables. The robust observed power values reaching 1.000 for CBE indicate a high likelihood of detecting true effects, thus minimising the risk of Type II error. Additionally, parameter estimates in Table 26 show that each predictor positively contributes to JP. CBE has the strongest coefficient (0.594), while DT (0.096) and EME (0.145) also show positive but less pronounced effects. These results reinforce CBE as the most influential factor, with DT and EME playing supportive but significant roles in enhancing JP.

Table 25: Full Factorial GLM Tests of Between Subjects Effects

Tests of Between-Subjects Effects - Dependent Variable: JP								
Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[b]
Corrected	164	3	54,6	323	<0,001	0,710	970	1,000
Intercept	4,32	1	4,32	25,6	<0,001	0,061	25,6	0,999
DT	1,71	1	1,71	10,1	<0,002	0,025	10,1	0,888
CBE	34,8	1	34,8	206	<0,001	0,342	206	1,000
EME	2,50	1	2,50	14,8	<0,001	0,036	14,8	0,970
Error	66,8	396	0,169					
Total	7570	400						
Corrected Total	231	399						

a. R Squared = 0,710 (Adjusted R Squared = 0,708)

Source: Author's illustration of results generated by SPSS

Table 26: Full Factorial Parameter Estimates

Parameter Estimates - Dependent Variable: JP									
Parameter	B	Std. Error	t	Sig.	95% Confidence Interval		Partial Eta Squared	Noncent. Parameter	Observed Power[a]
					Lower Bound	Upper Bound			
Intercept	0,612	0,121	5,06	<0,001	0,374	0,850	0,061	5,06	0,999
DT	0,096	0,030	3,18	<0,002	0,037	0,155	0,025	3,18	0,888
CBE	0,594	0,041	14,4	<0,001	0,512	0,675	0,342	14,4	1,000
EME	0,145	0,038	3,85	<0,001	0,071	0,218	0,036	3,85	0,970

Source: Author's illustration of results generated by SPSS

5.6.2.2 Spearman's Rank and Kendall's Tau Correlations

The Spearman's Rho Correlation results are shown in Table 27 and Kendall's Tau Correlation results in Table 28, whilst Figure 24 shows a summary of the hypotheses results.

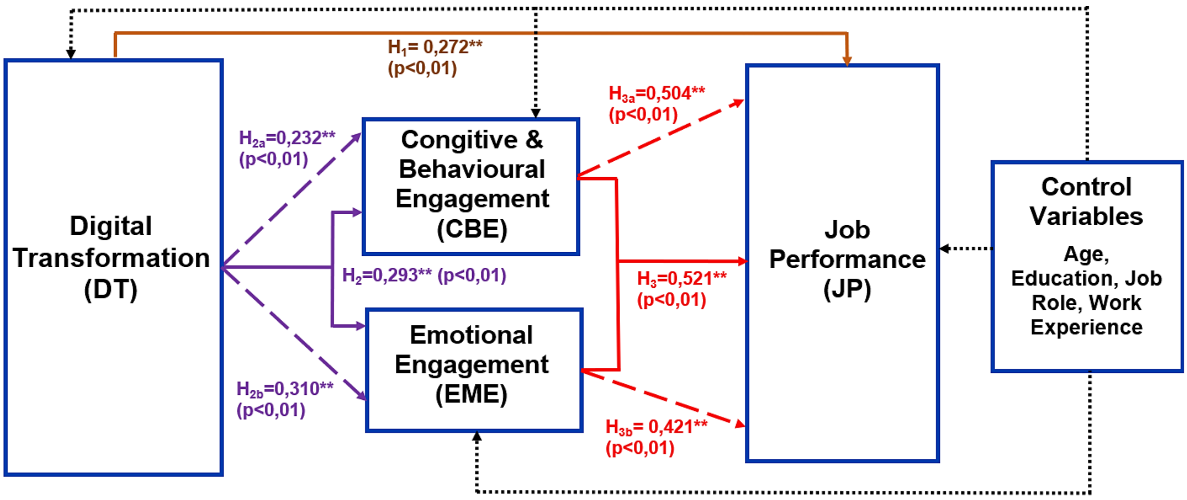

Figure 24: Research model with hypotheses testing results
Source: Author's illustration

Table 27: Spearman's Rho Correlation Results

Spearman's Rho Correlations						
		DT	**EE**	**CBE**	**EME**	**JP**
DT	Correlation Coefficient	1	**H2:** 0,387**	**H2a:** 0,306**	**H2b:** 0,394**	**H1:** 0,356**
	Sig. (2-tailed)		<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400
EE	Correlation Coefficient	**H2:** 0,387**	1	0,888**	0,844**	**H3:** 0,659**
	Sig. (2-tailed)	<0,001		<0,001	<0,001	<0,001
	N	400	400	400	400	400
CBE	Correlation Coefficient	**H2a:** 0,306**	0,888**	1	0,545**	**H3a:** 0,632**
	Sig. (2-tailed)	<0,001	<0,001		<0,001	<0,001
	N	400	400	400	400	400
EME	Correlation Coefficient	**H2b:** 0,394**	0,844**	0,545**	1	**H3b:** 0,534**
	Sig. (2-tailed)	<0,001	<0,001	<0,001		<0,001
	N	400	400	400	400	400
JP	Correlation Coefficient	**H1:** 0,356**	**H3:** 0,659**	**H3a:** 0,632**	**H3b**: 0,534**	1
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	
	N	400	400	400	400	400

**. Correlation is significant at the 0.01 level (2-tailed).

Source: Author's illustration of results generated by SPSS

The hypothesis results across all tested models reveal consistent relationships among the constructs. However, the Kendall's Tau results are more conservative, providing a more stringent perspective on these relationships. Consequently, this study places primary emphasis on Kendall's Tau outcomes to reduce the likelihood of overestimating the relationships in the analysis. Therefore, the subsequent discussion of results is grounded in the findings derived from Kendall's Tau Correlation.

The correlations for each hypothesis show statistically significant relationships at $p < 0.05$. For H1 (DT and JP relationship), a correlation of 0.272** suggests a moderate association, supporting the predicted relationship. Hypothesis H2 (DT and EE relationship) has a slightly stronger correlation at 0.293**, indicating a moderately positive relationship. Within the sub-hypotheses, H2a (DT and CBE relationship) shows a moderate correlation of 0.232**, while H2b (DT and EME relationship) displays a stronger correlation of 0.310**, both affirming the relationships expected in these hypotheses.

Table 28: Kendall's Tau Correlations Between Main Constructs

Kendall's Tau Correlations

		DT	EE	CBE	EME	JP
DT	Correlation Coefficient	1	**H2:** 0,293**	**H2a:** 0,232**	**H2b:** 0,310**	**H1:** 0,272**
	Sig. (2-tailed)		<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400
EE	Correlation Coefficient	**H2:** 0,293**	1	0,782**	0,725**	**H3:** 0,521**
	Sig. (2-tailed)	<0,001		<0,001	<0,001	<0,001
	N	400	400	400	400	400
CBE	Correlation Coefficient	**H2a:** 0,232**	0,782**	1	0,437**	**H3a:** 0,504**
	Sig. (2-tailed)	<0,001	<0,001		<0,001	<0,001
	N	400	400	400	400	400
EME	Correlation Coefficient	**H2b:** 0,310**	0,725**	0,437**	1	**H3b:** 0,421**
	Sig. (2-tailed)	<0,001	<0,001	<0,001		<0,001
	N	400	400	400	400	400
JP	Correlation Coefficient	**H1:** 0,272**	**H3:** 0,521**	**H3a:** 0,504**	**H3b:** 0,421**	1
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	
	N	400	400	400	400	400

**. Correlation is significant at the 0.01 level (2-tailed).

Source: Author's illustration of results generated by SPSS

Hypothesis H3 (EE and JP relationship) reveals the most substantial correlation at 0.521**, suggesting a strong association and this relationship also holds well in the sub-hypotheses.

H3a (CBE and JP relationship) correlates at 0.504**, and H3b (EME and JP relationship) shows a moderately strong correlation of 0.421**. These findings suggest varying levels of association between the constructs, indicating that EE mediates the relationship between DT and JP.

The Spearman's Rho Correlation results and Kendall's Tau Correlation results align with the full factorial generalised linear model results affirming varying levels of association between the constructs, which support the study's hypotheses and provide a robust foundation for further analysis.

5.6.2.3 EE's Mediating Effect on DT-JP Relationship

In the previous section, Kendall's Tau correlations confirmed significant relationships between DT and EE, as well as between EE and JP, highlighting EE's pivotal role as a mediator. This mediating effect was further validated through bootstrapping in a linear regression analysis, with detailed results presented in Tables 29, 30, and 31. Using bootstrapping within a linear regression framework allows for a robust analysis of indirect effects, offering insights into the extent of EE influence on the DT-JP relationship. This method provides an empirical basis to assess the significance and strength of mediation, enabling a comprehensive evaluation of EE's role in translating technological advancements into improved JP.

The model summary Table 29 highlights the significant impact of DT on JP and emphasises the mediating role of EE comprising CBE and EME with both models 1 and 2 having a value of $p < 0.05$. In model 1, DT alone explains 35.3% (R^2) of the variance in JP, indicating a moderate positive effect. However, model 2 shows a substantial improvement, with DT, EME, and CBE collectively accounting for 71.0% (R^2) of the variance. This increase emphasises the importance of EME and CBE in enhancing the relationship between DT and JP. The additional 35.7% (R^2 change) variance explained by these mediators demonstrates their critical role in translating DT efforts into improved JP. The Durbin-Watson statistic of 2.121 confirms no significant autocorrelation, supporting the reliability of the analysis. Overall, the findings suggest that, while DT has a direct positive impact on JP, the inclusion of EME and CBE significantly amplifies this effect, highlighting the value of fostering engagement and behavioural enablers alongside digital initiatives.

Table 29: Constructs and Mediators Linear Regression Model

Linear Regression Model Summary[c]										
					Change Statistics					
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	0,594[a]	0,353	0,351	0,612	0,353	217,2	1	398	<0,001	
2	0,843[b]	0,710	0,708	0,411	0,357	244,0	2	396	<0,001	2,12

a. Predictors: (Constant), DT---- b. Predictors: (Constant), DT, EME, CBE----- c. Dependent Variable: JP

Source: Author's illustration of results generated by SPSS

The excluded variables Table 30 highlights the potential contributions of CBE and EME to the dependent variable, JP. Both variables show strong relationships with JP, as evidenced by their t-values of 21.4 (CBE) and 13.6 (EME), which are highly significant at $p < 0.05$. The partial correlations of 0.732 and 0.565 for CBE and EME, respectively, indicate substantial individual associations with JP, even when controlling for other predictors already included in the model. Additionally, the collinearity statistics, with tolerance values of 0.63 (CBE) and 0.659 (EME), confirm that both variables have acceptable levels of multicollinearity, suggesting their inclusion in the model would not compromise their stability. These results underline the significance of CBE and EME as key mediators in the relationship between DT and JP, reinforcing their theoretical importance in enhancing JP in the context of DT.

Table 30: Excluded Mediator Variables

Excluded Variables[a]									
						Collinearity Statistics			
Model		Beta In	t	Sig.	Partial Correlation	Tolerance	VIF	Minimum Tolerance
1	CBE	0,742[b]	21,4	<0,001	0,732	0,630	1,59	0,630
	EME	0,560[b]	13,6	<0,001	0,565	0,659	1,52	0,659

a. Dependent Variable: JP----b. Predictors in the Model: (Constant), DT

Source: Author's illustration of results generated by SPSS

In addition to the linear regression model, the bootstrap results in Table 31 shed light on the intricate relationships among DT, EME, CBE, and JP. In model 1, DT demonstrates a significant positive effect on JP ($B = 0.512$, $p < 0.001$), with a 95% confidence interval (CI) of [0.357, 0.637], affirming the robustness of this relationship. However, in model 2, which incorporates CBE and EME as mediators, the direct effect of DT on JP diminishes ($B = 0.096$, $p = 0.014$, CI: [0.013, 0.178]), signifying weak but significant mediation. Among the mediators, CBE exerts the most substantial influence on JP ($B = 0.594$, $p < 0.001$, CI: [0.479, 0.690]), while EME also plays a meaningful role ($B = 0.145$, $p = 0.005$, CI: [0.052, 0.243]). These findings underscore the pivotal role of the EE construct in bridging the impact of DT on JP, with both CBE and EME serving as essential mediators. The narrow confidence intervals and negligible bias values further highlight the precision and reliability of the results.

Table 31: Boostrap Coefficients

Bootstrap for Coefficients							
		B	Bias	Std. Error	Boostrap[a] Sig. (2-tailed)	95% Conf. Interval Lower	Upper
1	(Constant)	2,171	0,018	0,322	0,001	1,616	2,852
	DT	0,512	-0,004	0,073	0,001	0,357	0,637
2	(Constant)	0,612	0,011	0,207	0,002	0,298	1,091
	DT	0,096	-0,001	0,039	0,014	0,031	0,178
	CBE	0,594	-0,002	0,054	0,001	0,479	0,690
	EME	0,145	0,001	0,049	0,005	0,052	0,243

a. Unless otherwise noted, bootstrap results are based on 1000 bootstrap samples

Source: Author's illustration of results generated by SPSS

These findings underscore the crucial role of EE in strengthening the positive impact of DT on JP, offering robust statistical support for the mediation between DT, EE, and JP. By investigating these additional factors, the study could determine the hypothesis.

5.6.2.4 Correlations Between Constructs and Control Variables

Following the hypotheses testing, the study examined the impact of control variables on DT, EE and JP constructs through Kendall's Tau correlation to gain a deeper understanding of how demographic and situational factors, such as age, education level, job role, and work experience, might influence DT efforts, engagement and performance outcomes. This analysis aimed to assess whether these control variables had any significant effect on the relationships if particular demographic or role-based characteristics moderated the constructs, providing a more comprehensive view of how DT, EE and JP may vary across different subgroups within the workforce. Table 32 presents the outcomes of the associations between the constructs and the control variables.

The results show varied associations between constructs and control variables. Age has a positive association with EE at 0.105** (p = 0.008) and with JP at 0.087* (p = 0.026). Education showed a negative association with the EE construct at -0.109** (p=00.5), cognitive and behavioural engagement (CBE) at -0.125** (p = 0.002) and JP at -0.105** (p = 0.007). However, the job role and work experience did not display any significant direct associations or correlations with any of the constructs.

Table 32: Kendall's Tau Correlations Between Key Constructs and Control Variables

Kendall's Tau Correlations for Demographic Information						
		DT	EE	CBE	EME	JP
Age	Correlation Coefficient	0,005	0,105**	0,069	0,018	0,087*
	Sig. (2-tailed)	0,906	0,008	0,084	0,678	0,026
	N	400	400	400	400	400
Educational Level	Correlation Coefficient	-0,012	-,109**	-,125**	-0,026	-,105**
	Sig. (2-tailed)	0,756	0,006	0,002	0,557	0,007
	N	400	400	400	400	400
Job Role	Correlation Coefficient	-0,035	-0,001	-0,054	0,033	-0,037
	Sig. (2-tailed)	0,375	0,989	0,170	0,451	0,342
	N	400	400	400	400	400
Work Experience	Correlation Coefficient	0,006	-0,014	-0,011	-0,077	0,047
	Sig. (2-tailed)	0,869	0,714	0,786	0,078	0,227
	N	400	400	400	400	400

**. Correlation is significant at the 0.01 level (2-tailed).
*. Correlation is significant at the 0.05 level (2-tailed).

Source: Author's illustration of results generated by SPSS

The following sections present an in-depth analysis of the different behaviours exhibited by various groups regarding the constructs using the Kruskal-Wallis test. This analysis provides a detailed view of how different population segments may respond differently to DT, EE and JP initiatives. The Kruskal-Wallis test, a non-parametric method, is specifically used here due to its robustness with non-normally distributed data, making it well-suited for handling the non-parametric nature of this dataset.

5.6.2.5 Association Between Age and Key Constructs

The findings in Table 33 indicate that most constructs, such as DT, EE, CBE and job JP, show no significant variation across age categories, with p-values exceeding 0.05. This lack of significant difference suggests that factors like age do not substantially impact these constructs, implying that perceptions of DT, engagement in cognitive and behavioural terms, and JP remain consistent across age groups.

Table 33: Age and Constructs Association Test Results

	Independent-Samples Kruskal-Wallis Test Summary - Age and Key Constructs		
	Null Hypothesis	Sig.[a,b]	Decision
1	The distribution of DT is the same across categories of Age (in years).	0,099	Retain the null hypothesis.
2	The distribution of EE is the same across categories of Age (in years).	0,096	Retain the null hypothesis.
3	The distribution of CBE is the same across categories of Age (in years).	0,386	Retain the null hypothesis.
4	The distribution of EME is the same across categories of Age (in years).	0,022	Reject the null hypothesis.
5	The distribution of JP is the same across categories of Age (in years).	0,053	Retain the null hypothesis.

Source: Author's illustration of results generated by SPSS

However, EME differs significantly across age groups, as shown by a p-value of 0.022, leading to the rejection of the null hypothesis. This suggests that EME is uniquely affected by age, possibly reflecting generational differences or varying professional priorities. Pairwise comparisons in Table 57 in Appendix 5 reveal specific age-related differences, particularly between younger employees (18-29) and older groups (50-59 and over 60), as well as between those aged 30-39 and the same older groups. These variations highlight potential differences in emotional connection to work among age groups, suggesting that age-specific engagement strategies may be beneficial for optimising EME in the workforce.

5.6.2.6 Association Between Educational Level and Key Constructs

The analysis of the educational level and its association with key constructs reveals notable patterns in Table 34. DT shows no significant variation across educational categories (p = 0.951), suggesting that educational background does not meaningfully influence perceptions or engagement with DT initiatives. However, the full EE construct varies significantly across educational levels, with a p-value of 0.032, rejecting the null hypothesis. Similarly, CBE also shows a statistically significant difference across educational levels (p = 0.007), indicating that these forms of engagement may be influenced by varying educational experiences or training. This highlights a potential need to consider educational diversity in strategies aimed at fostering engagement, particularly cognitive and behavioural elements, to ensure inclusivity and relevance across different educational backgrounds.

Table 34: Educational Level and Constructs Association Test Results

Independent-Samples Kruskal-Wallis Test Summary - Educational Level and Key Constructs			
	Null Hypothesis	Sig.[a,b]	Decision
1	The distribution of DT is the same across categories of Educational Level.	0,951	Retain the null hypothesis.
2	The distribution of EE is the same across categories of Educational Level.	0,032	Reject the null hypothesis.
3	The distribution of CBE is the same across categories of Educational Level.	0,007	Reject the null hypothesis.
4	The distribution of EME is the same across categories of Educational Level.	0,029	Retain the null hypothesis.
5	The distribution of JP is the same across categories of Educational Level.	0,001	Reject the null hypothesis.

Source: Author's illustration of results generated by SPSS

Further analysis, seen in Tables 58 and 59 in Appendix 5, shows pronounced variations in EE and CBE between individuals with postgraduate degrees versus those with diplomas and between bachelor's degree holders and those with lower qualifications, such as matric or diplomas. JP also differs significantly across educational categories ($p = 0.001$), with Table 60 indicating notable differences, particularly between those holding bachelor's degrees and diplomas and postgraduate degree holders versus diploma holders. These findings suggest that higher education levels may equip individuals with skills or perspectives that enhance JP and certain forms of engagement, underscoring the importance of tailoring organisational practices to align with the educational composition of the workforce.

5.6.2.7 Association Between Job Role and Key Constructs

The association analysis between job roles and the key constructs in Table 35 offers valuable insights into how varying responsibilities and organisational influence may shape perceptions of engagement and performance. The findings reveal no significant variation in perceptions of DT across job roles ($p = 0.046$), suggesting a relatively uniform view of DT initiatives regardless of role level. However, EE varies significantly by job role ($p = 0.014$), indicating that different levels of responsibility and organisational influence, as seen between specialists and senior managers, influence how employees engage emotionally with their roles. This observation, supported by Table 61 in Appendix 5, suggests that senior managers and specialists may require more tailored engagement strategies to address the specific emotional drivers of their engagement.

Table 35: Job Role and Constructs Association Test Results

Independent-Samples Kruskal-Wallis Test Summary - Job Role and Key Constructs			
	Null Hypothesis	**Sig.[a,b]**	**Decision**
1	The distribution of DT is the same across categories of Job Role.	0,046	Retain the null hypothesis.
2	The distribution of EE is the same across categories of Job Rolel.	0,014	Reject the null hypothesis.
3	The distribution of CBE is the same across categories of Job Role.	0,007	Reject the null hypothesis.
4	The distribution of EME is the same across categories of Job Role.	0,015	Reject the null hypothesis.
5	The distribution of JP is the same across categories of Job Role.	0,021	Reject the null hypothesis.

Source: Author's illustration of results generated by SPSS

Furthermore, CBE and EME distribute differently with varying job roles, having p-values of 0.007 and 0.015, respectively. Tables 62 and 63 in Appendix 5 illustrate differences in engagement patterns, showing distinct variations between specialists and administrative staff, and between managers and administrative roles, particularly concerning CBE. EME illustrates varying engagement patterns between specialists and senior management and differences amongst various management levels. These differences imply that role-related factors, such as job complexity and autonomy, influence how employees cognitively and behaviourally connect with their tasks.

Additionally, JP differs significantly across job roles ($p = 0.021$), with Table 64 in Appendix 5 showing that both specialists and managers perform differently from administrative staff. These findings suggest that roles with higher levels of responsibility, such as specialist and managerial positions, might see greater engagement benefits from tailored strategies that align with their unique job functions and organisational impact. Customised engagement and performance strategies could drive higher productivity and satisfaction levels across different job roles, creating a more cohesive and high-performing workforce.

5.6.2.8 Association Between Work Experience and Key Constructs

The results in Table 36 show that across all work experience categories, there are no statistically significant differences in the distribution of key constructs, including DT, EE, CBE, EME and JP.

Table 36: Work Experience and Constructs Association Test Results

Independent-Samples Kruskal-Wallis Test Summary - Work Experience and Key Constructs

	Null Hypothesis	Sig.[a,b]	Decision
1	The distribution of DT is the same across categories of Work Experience.	0,550	Retain the null hypothesis.
2	The distribution of EE is the same across categories of Work Experience.	0,273	Retain the null hypothesis.
3	The distribution of CBE is the same across categories of Work Experience.	0,130	Retain the null hypothesis.
4	The distribution of EME is the same across categories of Work Experience.	0,361	Retain the null hypothesis.
5	The distribution of JP is the same across categories of Work Experience.	0,525	Retain the null hypothesis.

Source: Author's illustration of results generated by SPSS

Specifically, the p-values for each construct (DT at p = 0.550, EE at p = 0.273, CBE at p = 0.130, EME at p = 0.361, and JP at p = 0.525) fall above the 0.05 threshold, leading to the retention of the null hypothesis in each case. This consistency suggests that work experience does not appear to create varying perspectives on DT initiatives, engagement levels, or perceptions of JP.

The insignificant distribution of these constructs across the work experience category implies that, regardless of how long employees have been in their roles, they hold similar views on DT initiatives, engagement, and performance metrics. This stability across work experience suggests a potential universal perception of these constructs, irrespective of experience length, hinting that job-specific factors may play a more critical role than work experience alone in shaping attitudes toward DT and related engagement constructs.

5.7 Results Discussion Chapter Conclusion

The findings chapter explores the relationships between DT, EE, and JP. Reliability tests confirmed strong internal consistency, with Cronbach's alpha values exceeding the acceptable threshold. Pearson's correlation and exploratory factor analysis (EFA) supported constructs validity, which established significant correlations between items and their constructs while validating the factor structure. Assumption testing revealed non-normality and heteroscedasticity, necessitating the use of non-parametric tests.

Hypotheses testing, conducted via generalised linear models (GLM), Spearman's Rank and Kendall's Tau, consistently showed significant positive relationships between DT, EE, and JP. Kendall's Tau, chosen for its robust approach, confirmed EE's mediating role. The Kruskal-Wallis test identified significant demographic variations in EE and JP, particularly by age, education, and job roles, although DT perceptions remained consistent across groups.

Bootstrap analysis in the linear regression model further validated EE's mediating effect on the DT-JP relationship. While DT directly impacts JP, the inclusion of contextual behavioural engagement (CBE) and emotional engagement (EME) as mediators significantly enhanced this effect, with CBE exerting the greatest influence.

The findings highlight EE's pivotal role in maximising the benefits of DT on JP. They emphasise the importance of tailored engagement strategies and role-specific DT initiatives to enhance organisational performance, offering valuable insights for aligning DT efforts with workforce dynamics.

6. Chapter 6: Results Discussion

6.1 Introduction

The results discussion chapter delves into the interpretation of the study's key findings, building on the data outlined in the previous chapter and comparing it with the literature. This section critiques the relationships between DT, EE, and JP, guided by the tested hypotheses. It explores how these constructs interact, highlighting specific results from statistical analyses, including Kendall's Tau correlations and the Kruskal-Wallis test. By integrating insights from descriptive statistics, reliability and validity assessments, and hypothesis testing, this chapter provides a detailed evaluation of how DT initiatives and EE influence JP. The analysis also considers demographic factors, such as age, education level, and job roles, to uncover any nuanced patterns that may inform practical applications and theoretical contributions. This approach offers a well-rounded understanding of the factors driving engagement and performance within a digitally transforming workplace. Figure 25 shows the chapter's high-level overview.

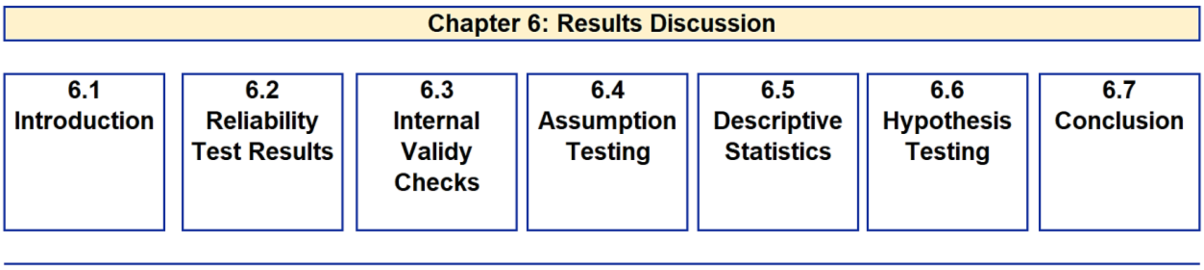

Figure 25: Chapter 6 summary structure
Source: Author's illustration

6.2 Reliability Test Results

Following the analysis of demographic descriptive statistics, Cronbach's Alpha tests were conducted to assess the internal consistency and reliability of the measurement scales used for each construct. A Cronbach's Alpha value of 0.70 or above is considered acceptable, indicating strong internal reliability among scale items (Hair et al., 2020; Pallant, 2020). This step ensures that each set of items within the constructs measures consistently, supporting the robustness of subsequent analyses.

The Cronbach's Alpha values for the constructs of DT, EE, and JP, as shown in Table 37, indicate high internal consistency, with coefficients of 0.886 for DT, 0.949 for EE, and 0.950 for JP. These values signify robust reliability for each construct, confirming that the items within each construct reliably measure the same underlying concept. A high alpha typically reflects a strong correlation among items (Hair et al., 2021). Cronbach's Alpha values exceeding 0.70 are considered acceptable, while values above 0.90 indicate excellent reliability, highlighting the instruments' consistency in capturing their respective constructs accurately (Taber, 2018). This reliability is particularly important in studies examining complex relationships, as it reinforces the internal validity of findings, especially when exploring the influence of DT on JP through EE.

Table 37: Reliability Test Results

Digital Transformation		Employee Engagement		Job Performance	
Cronbach's Alpha	0,886	Cronbach's Alpha	0,949	Cronbach's Alpha	0,950
No. of Items Before Test	5	No. of Items Before Test	12	No. of Items Before Test	13
No. of Items After Test	5	No. of Items After Test	12	No. of Items After Test	13

Source: Author's own illustration of results generated by SPSS

6.3 Constructs Validity Checks

After conducting reliability tests, the study proceeded with validity testing through bivariate correlation and exploratory factor analysis (EFA) to evaluate the measurement instrument's effectiveness in capturing the intended constructs. Validity testing through bivariate correlation confirmed that each construct item reflects its associated theoretical concept, serving as a preliminary indicator of validity (Hair et al., 2020). Following this, EFA was employed to identify underlying structural patterns among items, uncovering latent factors contributing to each construct's multidimensional nature. This process strengthens the study's assurance that the constructs exhibit both reliability and validity, ensuring they are accurate representations of the study's core concepts (Pallant, 2020; Tabachnick & Fidell, 2019). Testing across 30 items spanning three constructs further supported the suitability of these items in facilitating robust and reliable inferential analysis during the hypothesis-testing phase.

6.3.1 Pearson's Correlation Test Results

The study conducted validity tests on the DT, EE, and JP constructs using Pearson's bivariate correlation to examine the relationship between each item and the total construct score. This method, commonly used to verify internal consistency and construct validity, assesses whether each item within a construct correlates positively with the total score of that construct, reinforcing that the items measure a coherent underlying concept (Hair et al., 2020; Pallant, 2020).

As shown in Table 2 in section 5.4, the results display high and significant positive correlations ($p < 0.051$) for each item within the DT, EE, and JP constructs, indicating strong construct validity. The DT items show correlations with the total score ranging from 0.748 to 0.880, EE items from 0.612 to 0.902, and JP items from 0.617 to 0.872. These high correlations imply that individual items within each construct reliably measure their respective constructs, ensuring coherence and alignment with the theoretical model (Pallant, 2020; Tabachnick & Fidell, 2019). The complete results of Pearson's correlation analysis are provided in Appendix 4.

6.3.2 Exploratory Factor Analysis (EFA) Results

Following the establishment of construct validity using Pearson's bivariate correlation, the study employed Exploratory Factor Analysis (EFA) as a variable reduction technique. This approach identified the underlying factor structure of each construct, confirming that items grouped appropriately within their respective constructs and supporting the robustness of the instrument for subsequent analyses (Hair et al., 2020; Pallant, 2020). Table 19 presents the combined EFA outcomes for the DT, EE, and JP constructs, with the results for each construct discussed in the following subsections.

Table 19: Combined EFA Results – KMO and Bartlett's Test

Digital Transformation			Employee Engagement			Job Performance		
KMO Measure of Sampling Adequacy.		0,871	KMO Measure of Sampling Adequacy.		0,945	KMO Measure of Sampling Adequacy.		0,950
Bartlett's Test of Sphericity	Approx. Chi-Square	1096	Bartlett's Test of Sphericity	Approx. Chi-Square	4749	Bartlett's Test of Sphericity	Approx. Chi-Square	4032
	df	10		df	66		df	78
	Sig.	<0,001		Sig.	<0,001		Sig.	<0,001

Source: Author's own illustration of results generated by SPSS

6.3.2.1 Digital Transformation EFA

The DT EFA results in Table 19 demonstrate a solid factor structure, with a Kaiser-Meyer-Olkin (KMO) measure of 0.871, indicating excellent sampling adequacy for factor analysis. Bartlett's Test of Sphericity ($\chi^2 = 1096$, $p < 0.05$) also supports factorability, confirming strong correlations among the items. The extracted component, with an eigenvalue above 1, explains 69.1% of the variance, well above the 60% threshold that supports a unidimensional factor structure, consistent with theories of robust construct validity (Hair et al., 2020; Tabachnick & Fidell, 2019). Communalities are high, mostly exceeding 0.5, reinforcing that these items meaningfully represent DT.

The component matrix shows high factor loadings (ranging from 0.730 to 0.888) across all DT items, underscoring their alignment with a single, cohesive construct. The unrotated solution further implies a unidimensional structure, confirming that these items collectively measure DT as a unified concept, reflecting organisational dimensions like technology, culture, and strategy. This coherent structure affirms that DT can be reliably and validly measured within an organisation, aligning with contemporary findings on effective organisational change (Hair et al., 2020).

6.3.2.2 Employee Engagement EFA

The EE factor analysis results indicate a solid factor structure. A high KMO value of 0.945 and a significant Bartlett's Test of Sphericity ($\chi^2 = 4749$, $p < 0.05$) confirm that the variables correlate sufficiently for factor analysis. The first component explains 68.3% of the variance, with an additional 8.5% explained by the second, reaching a cumulative variance of 76.8%; a robust justification for retaining two components based on eigenvalues over 1.

The rotated component matrix presents high loadings, demonstrating item alignment with specific factors: cognitive engagement (CE) and behavioural engagement (BE) load on component 1, while emotional engagement (EME) items show shared loadings, suggesting overlap across components. Communalities exceed 0.7, signifying strong shared variance among items and reliable representation of the EE construct. Following Hair et al. (2020), these high communalities support convergent validity, as items meaningfully contribute to EE's multidimensional construct. This structure effectively captures the cognitive, emotional, and behavioural facets of engagement, providing a reliable measure for assessing employee involvement and informing engagement strategies (Saks, 2019).

6.3.2.3 Job Performance EFA

The JP construct validity results, with the Kaiser-Meyer-Olkin (KMO) measure of 0.950, signify excellent sampling adequacy, while Bartlett's Test of Sphericity ($\chi^2 = 4032$, $p < 0.05$) confirms sufficient inter-item correlations, making the data well-suited for factor analysis (Hair et al., 2020; Pallant, 2020). Communalities above 0.5 for JP items indicate meaningful contributions to the construct, reinforcing their reliability.

The variance analysis reveals that a dominant first component explains 63.17% of the total variance, suggesting a single-factor representation. This unidimensionality, supported by an eigenvalue above 1 and a total variance exceeding the 60% threshold, underscores that a single factor reliably captures the JP construct. Strong loadings in the component matrix confirm that all JP items align with this component, further supporting convergent validity and demonstrating the construct's coherence (Pallant, 2020; Hair et al., 2020). Overall, these results validate JP's robust unidimensional structure, suitable for single-factor analysis and measurement.

6.3.3 Revised Construct Components

After conducting an Exploratory Factor Analysis (EFA), only the EE construct split into two components: cognitive and behavioural engagement (CBE) and emotional engagement (EME), while the other constructs (i.e. DT and JP) retained their unidimensional structures. Table 15 in Section 5.3.3 presents the revised conceptual model, aligning with the EFA findings and includes hypotheses at both construct and sub-construct levels, denoted with subscripts "a" and "b" for clarity. The average scores of items within each construct and sub-construct formed total scores used for further analyses, including normality, homoscedasticity, and hypothesis testing.

6.4 Assumption Test Results Analysis

After completing the EFA, normality tests assessed whether the data distribution aligned with a normal curve (Pallant, 2020), while homoscedasticity tests checked the consistency of variances across variables to ensure unbiased results and robust interpretations (Hair et al., 2020). This section presents the results of the assumptions tests.

6.4.1 Normality Test Results Analysis

The normality tests for DT, EE and JP constructs reveal distributions that diverge notably from the normal curve. Q-Q plots and histograms in Figures 15, 16, 17 and 18 in Section 5.4.1 indicate deviations in upper and lower quantiles, signalling skewed distributions, while histograms further display a right-leaning data pattern with negatively skewed tails, suggesting a tendency for respondents to provide higher ratings. These patterns imply that participant responses are mostly positive, as reflected in the concentration of high values and negatively skewed distributions, although the skewness suggests the data may not align with normality assumptions.

Descriptive statistics enhance this understanding, showing high negative skewness and positive kurtosis values, which indicate pronounced peaks where responses cluster around specific values. The Kolmogorov-Smirnov and Shapiro-Wilk tests provide statistical confirmation, yielding p-values significantly below 0.05, reinforcing the non-normality of the distributions (Pallant, 2020; Hair et al., 2020). Standard deviations range from 0.760 to 0.883, pointing to consistent responses across items, while kurtosis values reveal a mix of sharp and moderate peaks, with item JP showing a notably high kurtosis of 9.04. This variance in kurtosis suggests varying degrees of response clustering around the mean.

Given these results, selecting appropriate statistical methods becomes essential; non-parametric tests may better account for the data's non-normal nature. These findings not only highlight a positive trend among respondents but also reveal important variances across constructs, warranting more granular exploration to fully capture respondent perspectives across the different measures (Pallant, 2020; Hair et al., 2020).

6.4.2 Homoscedasticity Test Results

The homoscedasticity test results reveal significant clustering of residuals in specific ranges, indicating heteroscedasticity and thus variability that is not consistent across the data. This deviation from the homoscedasticity assumption suggests that the residuals are not evenly distributed around the predicted values, potentially affecting the reliability of regression coefficients and statistical tests. When heteroscedasticity is present, regression models can produce biased estimates and misleading significance levels, compromising the accuracy of inferential conclusions (Pallant, 2020; Hair et al., 2020). This pattern suggests that variability in the data may shift across different levels of the independent variable, highlighting the importance of addressing heteroscedasticity to preserve the validity of the results. Adjusting for this, such as through robust standard errors, can help ensure that interpretations are both accurate and dependable for further analyses (Hair et al., 2021).

6.5 Descriptive Statistics Results Analysis

6.5.1 Constructs Data Descriptive Statistics

6.5.1.1 High-Level Data Descriptive Statistics

The descriptive statistics for the constructs presented in Table 19 in Section 5.5.1.1 show high levels of agreement among respondents, with each construct showing a strong central tendency and relatively low standard deviations. This suggests respondents uniformly understand and relate to the items within each construct, indicating reliability and consistency in measurement.

For the DT construct, the mean of 4.13, along with the mode of 5.00 and a low standard deviation (0.883), suggests respondents agree with the items related to DT, despite some response variation. This finding aligns with recent studies highlighting digitalisation as a critical driver of productivity and efficiency within organisations (Hair et al., 2020; Zomer et al., 2020). Hypothesis testing anticipated DT as a primary contributor to outcomes in the DT-JP-EE relationship, as digital technologies often facilitate streamlined work processes and increased job satisfaction (Bresciani et al., 2021).

The EE construct displays the highest mean (4.40), with a median of 4.70 and a mode of 4.80, indicating strong agreement and minimal response variation (standard deviation of 0.783). This finding suggests that employees feel highly engaged in their roles, aligning with research on the positive impact of EE on JP, specifically through enhanced motivation and job satisfaction (Saks, 2019). Consequently, EE played a pivotal role in hypothesis testing regarding DT and JP, given that engaged employees tend to perform better and demonstrate increased motivation and commitment.

The CBE sub-construct, with a mean of 4.47 and a mode of 5.00, points to high levels of employee commitment to their work, with a consistent response pattern (standard deviation of 0.811). This finding supports the theoretical basis of CBE as a performance driver, where cognitively and behaviourally engaged employees are more likely to exhibit enhanced performance and productivity (Bakker & Demerouti, 2017). Consequently, CBE significantly influenced the testing of the EE-JP relationship.

EME, though exhibiting slightly more variation (standard deviation of 0.874), still shows positive results with a mean of 4.29. The relatively high central tendency reflects that employees maintain a strong emotional connection to their work. Recent literature underscores EE as a predictor of JP, particularly in settings that emphasise psychological safety and employee well-being (Bakker & Albrecht, 2018). Therefore, the study anticipated EME to be a substantial contributor to the EE-JP relationship, reinforcing the importance of emotional investment in driving superior performance.

Finally, JP, with a mean of 4.28 and a mode of 4.80, indicates strong agreement among respondents, suggesting employees feel confident in their performance. The low standard deviation of 0.760 supports the notion of consistent performance across the sample. The study anticipated that both DT and EE, given that enhanced digital capabilities and higher engagement often correlate with improved performance outcomes, would positively influence JP (Bakker et al., 2020; Saks, 2019).

Therefore, the high means and low standard deviations for DT, EE, CBE, and JP indicate strong and consistent responses across these constructs, suggesting that they will significantly contribute to hypothesis testing. Specifically, the study expected DT to positively influence both EE and JP, while EE and CBE were anticipated to drive improved JP outcomes.

6.5.1.2 Digital Transformation Descriptive Statistics

The descriptive statistics for the DT items in Table 20 in Section 5.5.1.2 indicate a generally high level of agreement among respondents, with slight variation in some responses. Item DT2, focusing on the organisation's efforts to collect large amounts of data from different sources, scored the highest mean of 4.25, suggesting strong agreement and minimal variation (STD = 1.076). This indicates that respondents perceive data collection as a key aspect of DT, aligning with research findings that emphasise the role of data-driven decision-making in enhancing operational efficiency and performance (Zomer et al., 2020; Bresciani et al., 2021). Given its high mean and low standard deviation, the study expected DT2 to contribute the most to the overall DT construct score in the hypothesis testing.

Similarly, DT5, which pertains to the organisation's aim to achieve information exchange through digitalisation, also received a high mean score (4.23) and minimal variation (STD = 1.039). This item, like DT2, reflects the importance of seamless information flow in DT efforts. The role of information exchange in driving innovation and improving collaboration is well-documented in the literature, where it is recognised as essential for enhancing efficiency and fostering a culture of continuous improvement (Akter et al., 2024). Therefore, the study expected DT5 to be another significant contributor to the DT construct in the hypothesis testing.

Items DT1 and DT3 scored averages of 4.08 and 4.12, respectively, indicating moderate levels of agreement. While these scores reflect a positive outlook towards the organisation's digitalisation goals, they exhibit slightly more variation in responses (STDs of 1.081 and 1.058). This suggests that, while respondents generally agree with the digitalisation efforts, there may be differing opinions on the extent or effectiveness of such initiatives in the organisation. These items still contribute to the DT construct but may have a lesser impact compared to DT2 and DT5.

Finally, DT4, which addresses enhancing customer interface through digitalisation, had the lowest mean score of 3.97, indicating less agreement and a higher spread in responses (STD = 1.069). This may suggest that respondents are less convinced about the significance or effectiveness of digitalisation in improving customer interactions, which could reflect challenges in fully realising the benefits of digital technologies in customer-facing functions. This item might contribute the least to the overall DT construct score, potentially highlighting an area for improvement in the organisation's DT strategy.

Therefore, the items DT2 and DT5 are likely the most significant contributors to the DT construct score, given their high mean scores and low variability. These items reflect crucial aspects of DT, such as data collection and information exchange, which are pivotal for organisational growth and innovation (Akter et al., 2024; Zomer et al., 2020). As such, they will play an important role in the hypothesis testing, particularly in examining how DT impacts EE and JP.

6.5.1.3 Employee Engagement Descriptive Statistics

6.5.1.3.1 Cognitive and Behavioural Engagement

The results for the cognitive engagement (CE) and behavioural engagement (BE) items in Table 21, Section 5.5.1.3, reveal a high degree of engagement among respondents, with most items indicating strong agreement. Items such as CE3 ("I give my job responsibility a lot of attention") and BE2 ("I am willing to put in extra effort without being asked") achieve the highest means, 4.63 and 4.56 respectively, accompanied by low standard deviations. These results indicate that employees demonstrate consistently high cognitive and behavioural engagement. Similarly, CE2 ("I concentrate on my job when I am at work"), with a high mean of 4.45, further underscores the intense mental and behavioural dedication employees invest in their roles. Recent research corroborates these findings, showing that high cognitive and behavioural engagement levels are critical in enhancing organisational commitment and motivation (Saks, 2019; Bakker & Albrecht, 2018).

The results further support that employees exhibit high focus and mental investment in their work, key drivers for overall EE. The elevated levels of cognitive engagement noted in CE3 and CE2 suggest that employees are particularly engaged in tasks demanding concentration and mental effort, contributing positively to performance outcomes. This confirms studies indicating that cognitive engagement is essential for achieving sustained task-focused attention, which directly impacts productivity and performance (Bakker et al., 2020; Saks, 2019). Likewise, behavioural engagement items like BE2 and BE3 underscore employees' willingness to exert extra effort, consistent with recent findings that show employees who engage in discretionary effort often achieve superior JP (Saks, 2019; Bakker & Demerouti, 2017).

These findings significantly support the hypotheses for the EE construct, where high levels of cognitive and behavioural engagement reflect overall EE. This strengthens the connection between CE and BE as essential contributors to EE. High engagement levels in CE3 and BE2 are expected to positively impact hypotheses on DT and its influence on EE. The data confirms contemporary studies emphasising that employees mentally and behaviourally committed to their roles contribute to enhanced organisational performance, especially in settings embracing DT (Bakker & Albrecht, 2018; Zomer et al., 2020).

6.5.1.3.2 Emotional Engagement

The descriptive statistics for the emotional engagement (EME) items in Table 22, also in Section 5.5.1.3, show strong emotional connections to the organisation, though with some variation. EME4 ("I care about the future of my company") and EME3 ("I believe in the mission and purpose of my company") have the highest means (4.55 and 4.31, respectively), indicating that employees feel a strong emotional bond with the organisation's future and values. The low standard deviations for these items (0.938 and 1.027) suggest that responses are relatively consistent, indicating that a significant portion of the workforce feels emotionally engaged with the company's purpose.

EME1 ("Working at my current organisation has a great deal of personal meaning to me") also shows strong engagement with a mean of 4.24, but with a slightly higher standard deviation of 0.999, reflecting more variation in emotional attachment. EME2 ("I feel a strong sense of belonging to my job") has the lowest mean (4.01) and the highest standard deviation (1.078), suggesting that while some employees strongly feel a sense of belonging, others are less emotionally connected to their job, resulting in a more diverse range of responses.

These findings suggest that the EME construct is strongly represented by items such as EME4 and EME3, which show high means and consistency in responses. These items are likely to contribute significantly to the EE construct, particularly in terms of emotional commitment. As emotional engagement is a critical driver of overall EE, these results support the hypothesis that higher EME leads to greater overall engagement (Saks, 2019).

Employees who care deeply about the future of the company and believe in its mission are more likely to be engaged in their roles, which can positively influence performance outcomes and retention (Bakker & Albrecht, 2018). Therefore, EME contributes meaningfully to EE and supports the broader hypothesis that emotional attachment enhances overall EE.

6.5.1.4 Job Performance Descriptive Statistics

The descriptive statistics for the task performance (TP) and contextual performance (CP) items in Table 23, also in Section 5.5.1.4, indicate a strong consensus among employees regarding their self-assessed performance across various dimensions. For task performance, the items TP3 ("I keep in mind the results that I have to achieve in my work") and TP1 ("I manage to plan my work so that it is done on time") show the highest means (4.52 and 4.36, respectively), which reflect the importance of effective time management and a results-oriented approach. These attributes are critical to JP, as they demonstrate employees' capacity to focus on key outcomes and manage workloads efficiently, aligning with studies linking time management and prioritisation with enhanced performance outcomes (Bakker et al., 2020; Saks, 2019).

For contextual performance, the items CP3 ("I take on challenging work tasks, when available") and CP4 ("I work at keeping my job knowledge up-to-date") also reflect high means (4.43 and 4.38, respectively), suggesting that employees actively seek challenges and invest in their professional development. Such behaviours contribute positively to JP by increasing employees' ability to handle complex tasks and advance their skills, reinforcing findings that link proactive skill development and adaptability with improved job outcomes (Bakker & Demerouti, 2017; Tabachnick & Fidell, 2019). Additionally, CP6 ("I come up with creative solutions to new problems") and CP8 ("I actively participate in work meetings") highlight the importance of innovation and engagement within the workplace, both of which are integral to assessments of JP.

These results for TP and CP suggest that employees' capabilities in managing tasks effectively, embracing new challenges, and engaging in ongoing skill development significantly contribute to overall JP. The findings support research that shows how task efficiency and career development behaviours positively impact JP (Saks, 2019; Bakker et al., 2020). Proactive employees who continuously enhance their skills and actively participate in their roles are likely to achieve superior performance outcomes, reinforcing the hypothesis that high levels of task and career engagement lead to better overall JP.

6.5.2 Demographics Data Descriptive Statistics

The data analysis starts with descriptive statistics of demographic details to offer essential insights into the characteristics of the sample population. Age, education level, job role, and work experience significantly shape individuals' perspectives, adaptability to new initiatives, and receptivity to organisational changes like DT (Pallant, 2020). By describing the sample, this study can assess its representativeness and relevance to the study's objectives and identify demographic patterns that may impact the main constructs being examined, such as DT, EE, and JP (Hair et al., 2020). Descriptive statistics also support a clearer interpretation of later findings, allowing the researcher to contextualise outcomes within the demographic makeup of the participants (Hair et al., 2020).

6.5.2.1 Age Distribution Analysis

The age distribution in this study reveals a concentration of respondents between 30 and 49 years, with 39% in the 30–39 range and 32% in the 40–49 range. This mid-career demographic is significant, as such employees tend to possess the balance of experience and adaptability needed to embrace DT when well-engaged (Bakker & Demerouti, 2017; Saks, 2019). Mid-career professionals often have a strong foundation of skills and a readiness to incorporate digital technologies to enhance JP (Zomer et al., 2020). Although older employees (50–59 and above 60) may encounter more obstacles with new technologies, effective engagement strategies can reduce this resistance, ensuring they remain motivated to integrate DT in ways that improve both task and contextual performance (Nguyen et al., 2023; Bakker & Albrecht, 2018).

The majority of respondents fall within mid-career age brackets, indicating a workforce potentially comfortable adapting to DT. While younger employees, such as those aged 18–29, represent a smaller portion of the sample, they often bring tech-savviness and innovative thinking that aligns with DT initiatives (Saks, 2019; Zomer et al., 2020). In organisations, a balanced age range fosters diverse perspectives, which are essential for creating inclusive DT strategies that enhance processes and outcomes (Bakker & Demerouti, 2017). Engagement efforts tailored to older employees, such as focused training on digital technologies, can enhance their ease with technology, supporting a smooth and productive transformation process. Engagement in this context ensures employees remain motivated and prepared to integrate digital technologies into their workflows, positively influencing both task and contextual performance (Saks, 2019; Bakker et al., 2020).

6.5.2.2 Education Level Analysis

The respondents' qualifications range widely, with most holding tertiary-level education. Higher educational attainment supports adaptability to technological shifts, as employees with advanced qualifications exemplify the cognitive engagement required to learn and apply new technologies effectively (Bakker & Albrecht, 2018). In sectors like mining, where DT increasingly introduces new technologies and systems, employees with higher education levels are better equipped to engage in continuous skill development, making them more receptive to DT changes (Zomer et al., 2020; Bakker et al., 2020). This trend aligns with Saks' (2019) findings, which suggest that engagement excels among employees who feel competent to meet the demands of emerging technologies, ultimately enhancing their JP.

The respondents' educational profile suggests a workforce prepared to support successful DT efforts. Research indicates that educated employees are typically more open to change and have refined problem-solving abilities, which facilitate their adaptation to new DT systems and processes (Saks, 2019; Bakker & Demerouti, 2017). By fostering continuous learning and development, organisations can create an environment that values growth and supports innovation, essential elements for successful DT initiatives (Bakker & Albrecht, 2018). This emphasis on skill enhancement is crucial, as it not only improves individual EE but also strengthens organisational readiness for technological advances (Zomer et al., 2020).

6.5.2.3 Job Role Analysis

The data on job roles reveals a diverse workforce comprising both managerial and non-managerial positions. Research shows that employees in managerial roles exhibit higher engagement levels because of their greater autonomy and influence in decision-making, which supports smoother transitions during DT initiatives and positively impacts JP (Bakker & Albrecht, 2018; Saks, 2019). Managers are often instrumental in promoting DT, driving team support, and aligning DT goals with organisational objectives, all of which contribute to successful technology integration within their teams (Bakker & Demerouti, 2017; Zomer et al., 2020). Thus, when managers are highly engaged, they help bridge DT efforts with broader strategic goals, directly enhancing team performance outcomes.

For non-managerial employees, who may have limited autonomy, engagement strategies focused on leadership and strong support are essential to drive motivation and technology adoption. Saks (2019) highlights the crucial role of engagement for non-managerial roles in maximising DT's positive impact on organisational performance. Tailored engagement strategies, therefore, prepare and motivate employees at different levels to adapt to new processes.

The presence of a high percentage of specialists within the workforce suggests significant in-depth expertise, which is invaluable for DT efforts. Research suggests that involving specialists in DT processes not only leverages their knowledge for effective digital integration but also enhances engagement by recognising their contributions (Bakker et al., 2020; Zomer et al., 2020). Engaging specialists by involving them in planning and decision-making fosters ownership over DT initiatives, increasing their motivation and satisfaction (Saks, 2019). This expertise-driven approach to EE strengthens the quality of DT processes and ensures more relevant, well-received technological adaptations within the organisation.

6.5.2.4 Work Experience Analysis

The analysis reveals that most respondents possess extensive work experience, with a significant proportion reporting over ten years in the industry. This experienced demographic often brings substantial industry knowledge to DT but may initially resist adopting new technologies. However, Bakker and Albrecht (2018) and Saks (2019) suggest that well-engaged, experienced employees can exhibit high levels of emotional and behavioural engagement, essential for adaptability and performance improvement. Effective engagement strategies, such as ongoing training and strong leadership support, prove invaluable in encouraging these employees to use new technologies to improve JP (Bakker et al., 2020).

Younger or technically skilled employees are more likely to display elevated levels of behavioural and cognitive engagement, which positively impacts their use of digital technologies and enhances performance. Meanwhile, older or less tech-savvy employees may benefit from engagement efforts that address specific barriers to adaptation, such as tailored training and supportive leadership, to ensure a smoother integration into DT initiatives. This approach aligns with findings indicating that employees who feel valued and are given adequate support show improved engagement with DT, thereby maximising its impact on JP (Zomer et al., 2020; Saks, 2019).

Interestingly, many respondents have less than one year of experience in their current roles, which may present challenges for DT integration. This high prevalence of employees being new in their current roles may indicate an industry undergoing structural changes. Employees newer to their roles may feel heightened uncertainty and, consequently, more resistance to technological changes. For this group, fostering engagement is essential; clear communication and leadership transparency can reduce anxieties associated with DT. Building a sense of ownership among employees with new job roles, alongside actionable engagement strategies such as mentorship and feedback mechanisms, can enhance their outlook on DT, fostering greater openness to digital adoption (Bakker & Demerouti, 2017; Saks, 2019). Furthermore, Zomer et al. (2020) suggest that structured onboarding and support systems play a critical role in improving engagement and reducing resistance to change.

6.5.2.5 Demographics Information Summary

The data presents a comprehensive profile of the sample, comprising a well-educated, predominantly middle-aged workforce or mid-career professionals, and largely composed of specialists, with few respondents in senior managerial and executive roles, with varying degrees of experience. However, the high percentage of respondents with less than one year of experience in their current roles suggests a potential for change and adaptation within the organisation. This combination of factors may influence the overall culture, productivity, and the industry's DT strategies and their implementation. This demographic context is key to understanding the study's findings on how DT influences JP and EE, particularly as these professionals are likely involved in both the implementation and adaptation to new digital processes within the mining sector.

6.6 Hypotheses Testing

The study meticulously examined the relationships between DT, CBE, EME, and JP using a structured approach. The study initially considered three statistical methods; a generalised linear model (GLM), Spearman's Rank, and Kendall's Tau Correlations to test these relationships. Each method consistently produced similar outcomes, affirming the associations between constructs. However, the study ultimately chose Kendall's Tau correlations for the analysis because of its conservative nature, which helps mitigate the risk of overestimating effect sizes, thus providing a more restrained and reliable assessment of relationships within the dataset.

Beyond relationship testing, the study used the Kruskal-Wallis test to explore potential variances in DT, CBE, EME, and JP across different demographic and professional groups, including age, educational level, job roles, and work experience. This non-parametric test allowed for an examination of how these categorical variables influenced the primary constructs, adding further depth to the analysis by revealing whether significant differences existed across these groups. This comprehensive approach provided a robust framework for evaluating both direct relationships and the demographic impacts on engagement and performance constructs.

6.6.1 Study Hypotheses

The hypotheses testing outcomes in Table 38 reveal substantial support for the study's theoretical framework, confirming positive associations between DT, EE, and JP. The support for H1 highlights a positive link between DT and JP, suggesting that DT initiatives may enhance JP through increased efficiency and improved workflows (Zomer et al., 2020; Bakker et al., 2020). H2, along with its sub-hypotheses H2a and H2b, supports DT's positive relationships with EE, particularly in terms of CBE and EME. These results suggest that DT efforts may foster a sense of involvement and emotional connection among employees, consistent with findings by Saks (2019) and Bakker & Albrecht (2018).

Table 38: Hypotheses Testing Outcomes

Hypothesis	Relationship in The Model	Hypothesis Type	Testing Outcome
H1	DT has a positive association with JP	Relational	Supported
H2	DT has a positive association with EE	Relational	Supported
H2a	DT has a positive association with CBE	Relational	Supported
H2b	DT has a positive association with EME	Relational	Supported
H3	EE has a positive association with JP	Relational	Supported
H3a	CBE has a positive association with JP	Relational	Supported
H3b	EME has a positive association with JP	Relational	Supported

Source: Author's illustration

Furthermore, H3, H3a, and H3b confirm the positive influence of EE on JP, with both CBE and EME contributing to performance outcomes. These results align with studies showing that engagement, particularly when inclusive of cognitive and emotional elements, fosters higher JP by enhancing employees' focus, motivation, and dedication (Saks & Gruman, 2021; Bakker & Albrecht, 2018). These findings highlight the mediating role of EE in translating DT initiatives into tangible performance improvements. They also reinforce the importance of a multidimensional engagement approach, where employees' cognitive and emotional investment in their roles drives sustainable productivity gains. Detailed analyses and implications of these relationships will follow in subsequent sections, offering strategies to optimise DT and EE for enhanced organisational performance (Zomer et al., 2020).

6.6.2 Inferential Hypotheses Testing Results

Figure 24 presents the results of the hypotheses testing for the DT-JP, DT-EE and EE-JP relationships.

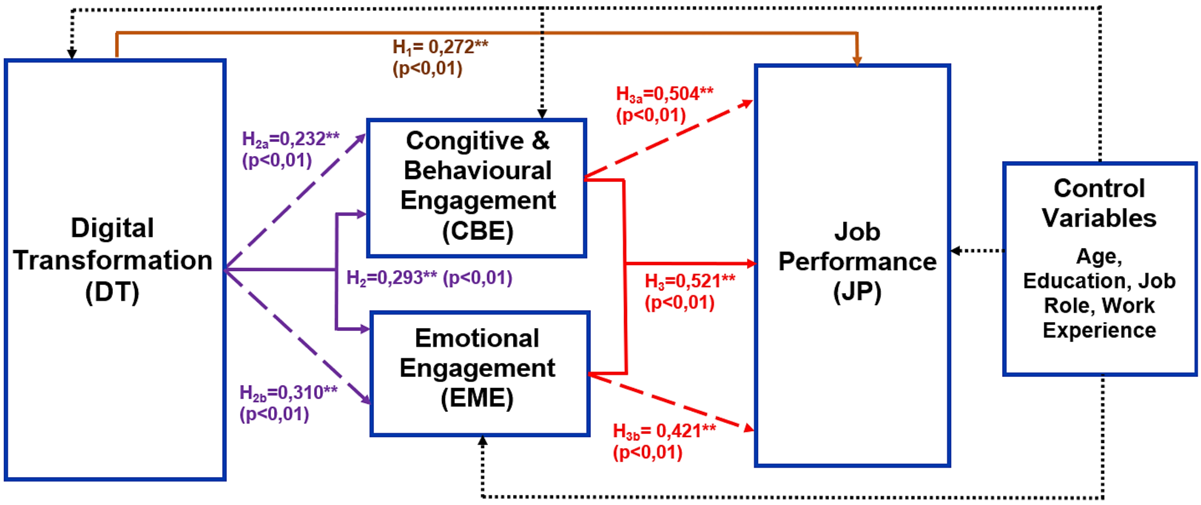

Figure 24: Research model with hypotheses testing results

Source: Author's illustration

The testing results show significant correlations across all three relationships, indicating that DT positively influences both EE and JP, with engagement acting as a key mediator. Specifically, DT is shown to have a moderate positive correlation with JP (r = 0.272**) and a slightly stronger correlation with EE (r = 0.293**), suggesting that DT enhances engagement, which in turn drives performance. The results also demonstrate a strong link between EE and JP (r = 0.521**), highlighting the critical role that engagement plays in improving JP. Additionally, the sub-components of engagement, CBE and EME, are both positively correlated with JP, with EME having a slightly stronger impact. These findings underscore the interconnected nature of these constructs and their combined influence on organisational outcomes. The following sections provide an in-depth analysis of the hypothesis findings.

6.6.2.1 DT and JP Relationship Analysis

The study's findings underscore the interconnectedness of DT, EE, and JP, highlighting the roles that CBE and EME play in moderating these relationships. In examining the DT-JP relationship (H1), the correlation of 0.272** points to a moderate association, supporting the hypothesis that DT positively impacts JP. From a theoretical perspective, the relationship between DT and JP aligns with the JD-R model, which posits that job resources such as autonomy, meaningful tasks, and feedback enhance employee performance when they help mitigate job demands and foster engagement (Bakker & Demerouti, 2017). DT facilitates this enrichment by automating routine and manual tasks, allowing employees more time and mental capacity to focus on higher-level, value-added activities (Zomer et al., 2020). In the mining industry, the implementation of automated technologies, such as autonomous haul trucks, excavation machines, and real-time monitoring systems, allows workers to oversee complex operations rather than engage in repetitive, physically demanding tasks. This shift not only improves operational efficiency but also enhances the perceived meaningfulness of the work, thereby boosting JP (Bakker et al., 2020; Zomer et al., 2020). These advancements allow employees to apply their skills in more impactful ways, ultimately leading to higher productivity and better JP outcomes (Saks, 2019; Zomer et al., 2020).

The practical implications for mining companies are significant. The incorporation of DT through automation, data analytics, and remote monitoring allows workers to shift from manual tasks to more cognitively engaging roles. For example, predictive maintenance systems that use real-time data to forecast equipment failures help reduce downtime and maintenance costs, enabling technicians to focus on proactive problem-solving rather than reactive repairs. Such systems directly impact JP by improving work quality and reducing the likelihood of errors. Furthermore, the availability of data-driven insights enhances workers' ability to make informed decisions, further optimising performance (Saks, 2019; Bakker et al., 2020). These advancements align with findings in recent studies, which highlight how DT fosters more efficient work practices and contributes to enhanced performance outcomes in resource-intensive sectors like mining (Bakker & Albrecht, 2018; Zomer et al., 2020).

Studies have also shown that digital technologies can support decision-making processes, thus improving JP. For example, research highlights that the introduction of digital technologies, including mobile applications and cloud-based systems, significantly enhances the decision-making capacity of employees in various industries, including mining (Zomer et al., 2020). These technologies provide real-time information, which allows workers to make more informed, timely decisions, leading to improved performance metrics such as productivity, safety, and cost efficiency (Zomer et al., 2020; Bakker et al., 2020). In the mining context, the use of geographic information systems (GIS) and predictive analytics for resource extraction or safety monitoring enhances the precision of operations, directly correlating with better performance outcomes (Zomer et al., 2020).

Furthermore, the introduction of DT is also likely to reduce the physical and mental workload of employees, which can alleviate stress and burnout, both of which are common barriers to optimal JP. Automation, for example, can reduce the physical strain on workers, while digital collaboration technologies can improve communication and reduce time spent on administrative tasks. This confirms findings that technology alleviating job demands without reducing the challenges of the work itself results in enhanced performance outcomes (Bakker & Demerouti, 2017; Saks, 2019). By reducing the cognitive load and allowing workers to focus on more impactful aspects of their roles, organisations are likely to see higher levels of engagement, satisfaction, and ultimately, performance (Bakker & Demerouti, 2017; Saks, 2019).

Mining organisations should focus on leveraging DT to not only improve operational efficiencies but also to create a work environment that fosters performance. This involves investing in technologies that streamline processes and increase the time employees can devote to higher-value work while ensuring proper training and support to help workers integrate new technologies effectively (Bakker et al., 2020; Zomer et al., 2020).

Therefore, the relationship between DT and JP, as identified in the study, highlights the transformative potential of digital technologies in enhancing JP. By automating routine tasks and providing employees with technologies that support decision-making, organisations in the mining industry can significantly improve productivity and efficiency. The implications of this relationship suggest that, as mining companies continue to implement DT, they should strategically align technological advances with the development of human capital to maximise both EE and JP.

6.6.2.2 DT and EE Relationship

The DT-EE relationship (H2) presents a slightly stronger correlation at 0.293**, indicating that DT significantly enhances engagement, which can be observed in the mining industry as well. Modernisation through DT often necessitates upskilling, fostering a culture of innovation and adaptability within the workforce. Specific to DT's effect on CBE (H2a, r=0.232**) and EME (H2b, r=0.310**), the findings suggest that while DT positively influences both cognitive-behavioural and emotional aspects of engagement, the emotional component is more strongly affected.

The theoretical underpinnings of this relationship can be examined through the lens of the job demands-resources (JD-R) model, which suggests that organisational resources such as new technologies can enhance EE by reducing job demands and offering opportunities for personal growth (Bakker & Demerouti, 2017). In the case of DT, technologies such as automation, real-time data systems, and advanced analytics can act as resources that not only improve operational efficiency but also engage employees cognitively and emotionally.

As employees see their work becoming more aligned with innovative and forward-thinking technologies, they feel a greater sense of involvement and pride in their roles, which directly impacts their overall engagement (Saks, 2019).

From a practical perspective, mining companies that prioritise DT are creating an environment that values innovation and adaptability. The introduction of new digital technologies encourages employees to engage in upskilling programmes, thereby enhancing CBE. However, the emotional aspect of engagement, as highlighted by the findings, plays a crucial role in sustaining long-term commitment and motivation. Targeted training, clear communication from leadership, and the creation of a psychologically safe environment where employees feel supported during transitions fosters EME. Research by Akter et al. (2024) supports this view, suggesting that providing employees with the resources and emotional support to navigate DT helps them feel valued, connected to their organisation, and motivated to contribute fully.

For example, the introduction of automation in mining operations, such as autonomous haul trucks or automated drilling systems, not only requires employees to acquire new technical skills (CBE) but also challenges their emotional connection to the work. Proper introduction of DT initiatives, with leadership ensuring open lines of communication, offering training, and emphasising the positive impact of these changes on the company's future, is likely to increase the emotional engagement of employees. In some cases, this emotional investment can lead to improved attitudes towards organisational change and a stronger commitment to the company's goals (Bakker et al., 2020; Saks, 2019).

The role of leadership is crucial in this dynamic. Leaders in mining companies must be proactive in fostering an emotionally supportive environment, ensuring that employees feel empowered and secure in their roles despite the changes introduced by DT. This could include creating spaces for employees to share their concerns, providing regular updates on the progress of digital integration, and recognising employees' efforts in adapting to new systems. By cultivating emotional engagement through these strategies, organisations can ensure that their workforce remains motivated and committed, thereby enhancing overall performance (Bakker & Albrecht, 2018; Zomer et al., 2020).

Research has shown that the impact of DT on EE is particularly evident in sectors undergoing significant technological transformation. In mining, for instance, companies like Rio Tinto have invested in digital technologies and remote operations, which have enhanced operational efficiency while also promoting a more engaged workforce (Zomer et al., 2020).

Similarly, a study by Barnewold and Lottermoser (2020) highlights that introducing advanced technologies in mining led to improved engagement levels, particularly when strong leadership support and targeted upskilling programmes accompanied implementation efforts.

Therefore, the relationship between DT and EE is pivotal in shaping EE, particularly in industries like mining. While both CBE and EME are positively impacted by DT, EME plays a more prominent role in driving overall engagement. Mining companies that strategically implement DT and pair it with strong emotional support structures can significantly enhance EE, ultimately leading to higher levels of performance and innovation. Theoretical models like JD-R, alongside real-world examples from the mining industry, demonstrate that DT not only improves operational outcomes but also cultivates a more motivated and engaged workforce.

6.6.2.3 EE and JP Relationship Analysis

The relationship between EE and JP (H3) reveals a significant correlation of 0.521**, the highest among the constructs, underscoring the strong connection between engagement and performance. This relationship is further supported by the strong correlations of the sub-components: CBE and JP (H3a) at 0.504**, and EME and JP (H3b) at 0.421**. These findings highlight that engaged employees; particularly those who demonstrate high levels of both CBE and EME, are more likely to exhibit higher JP.

Theoretically, this connection aligns with the job demands-resources (JD-R) model, which argues that when employees perceive their work as meaningful and have access to resources that support their tasks, their engagement, motivation, and JP improve (Bakker & Demerouti, 2017). In this context, CBE represents the active participation and mental energy that employees invest in their work. High CBE positively correlates with JP, as employees who are mentally engaged tend to be more productive, attentive, and efficient. EME, which encompasses employees' emotional connection to their work and organisation, also significantly influences performance. Employees who feel emotionally connected to their workplace are more likely to put in discretionary effort, showing resilience and commitment, especially during challenging periods.

From a practical perspective, organisations that focus on fostering high levels of engagement are more likely to see enhanced JP. In the mining industry, where workers often face physically demanding environments, remote or harsh conditions, and the need for high levels of safety, engagement plays a crucial role in performance. Engaged employees in mining operations are not only more motivated to meet performance targets but are also more resilient and adaptable when dealing with organisational changes or adverse conditions, such as fluctuating market prices or new technology implementation. For example, studies by Hooi and Chan (2023) show that employees who experience meaningful engagement are more likely to adapt successfully to transformative technologies and achieve higher performance outcomes.

This relationship between EE and JP is further illustrated by findings in other industries. For instance, Trenerry et al. (2021) demonstrate that engaged employees are better positioned to leverage digital tools, innovate, and maintain high performance even under significant organisational changes. Similarly, Bakker et al. (2020) highlight that proactive engagement strategies focusing on emotional and cognitive dimensions drive innovation and productivity, particularly in industries undergoing rapid technological transformation.

In mining, fostering EE can lead to improved performance through several practical initiatives. First, companies can invest in creating meaningful work experiences by ensuring employees feel their contributions matter to the broader organisational goals. For example, providing opportunities for employees to engage in decision-making processes or recognising their efforts publicly can enhance their emotional commitment and, by extension, their performance (Saks & Gruman, 2021; Albrecht et al., 2015). Additionally, by supporting the development of skills through training programmes, mining companies can boost employees' CBE, ensuring that employees cognitively invest in their roles. This approach aligns with the findings of Hooi and Chan (2023), who highlight that tailored training initiatives significantly enhance engagement, which contributes positively to performance.

The role of leadership in this relationship is also critical. Leaders who engage with their employees in a supportive, transparent, and empathetic manner tend to foster higher levels of both CBE and EME. Studies demonstrate that employees who participate in training and receive guidance from supportive leadership are more likely to embrace DT initiatives actively, rather than merely complying with them (Buil et. al., 2019; Hooi & Chan, 2023). Leaders who recognise employees' contributions, offer constructive feedback, and provide growth opportunities can significantly enhance engagement levels, thereby boosting performance (Bakker & Demerouti, 2021). This is particularly important in industries like mining, where safety, productivity, and innovation are paramount. Research has shown that effective leadership improves EE, resulting in higher performance outcomes and greater resilience in challenging environments (Albrecht et al., 2015; Trenerry et al., 2021).

Therefore, the significant relationship between EE and JP, as demonstrated by the strong correlations in the study, highlights the importance of fostering EE to enhance JP. Theoretical frameworks, such as the JD-R model, provide valuable insights into how engagement contributes to performance, while practical applications in industries like mining show that engaged employees are more adaptable, motivated, and resilient, especially when faced with organisational change. By prioritising engagement through both cognitive and emotional channels, mining companies can optimise JP, leading to improved productivity, safety, and innovation in the long term.

6.6.2.4 EE as a Mediator of DT and JP Relationship

The bootstrapping results in linear regression emphasise the mediating role of EE in the DT-JP relationship. While Kendall's Tau correlations confirmed significant positive relationships between DT and EE, as well as EE and JP, positioning EE as a pivotal mediator in translating the benefits of digital advancements into improved JP, bootstrapping within the linear regression framework further validated EE's mediating effect, providing robust evidence of its significance. These results confirm studies such as Akter et al. (2024), which emphasise that fostering engagement is crucial for leveraging the transformative potential of technology.

The analysis revealed that while DT independently accounts for 35.3% of the variance in JP (R^2), the inclusion of EE components, CBE and EME, raised the explanatory power to 71.0% (R^2). This substantial improvement highlights the amplified impact of DT on JP when mediated by CBE and EME, as supported by findings from Buil et al., (2019), which underscore the value of behavioural and emotional dimensions of engagement in driving performance outcomes.

The results from the excluded variables table further affirmed the importance of CBE and EME. With significant t-values of 21.4 (CBE) and 13.6 (EME) and strong partial correlations (0.732 and 0.565, respectively), these mediators demonstrated strong individual associations with JP. The acceptable collinearity statistics (tolerance values above 0.6) ensure their independent contributions to the model's stability, confirming insights from Kwon and Kim (2020), which advocate for integrating behavioural and emotional enablers to maximise the impact of digital initiatives.

The findings of this study underline that EE plays a pivotal role in mediating the impact of DT on JP. As organisations increasingly integrate DT initiatives such as automation, data analytics, and real-time monitoring, they create environments that can significantly influence employee experiences and outcomes. Engaged employees are more receptive to these technological shifts, as they are more likely to utilise new digital technologies to improve productivity, accuracy, and creativity in their roles (Akter et al., 2024; Buil et al., 2019). In the mining industry, DT empowers employees to transition from repetitive, manual tasks to more complex, value-adding activities, thereby enhancing their emotional and behavioural commitment and boosting JP (Bakker et al., 2020; Barnewold & Lottermoser, 2020). This shift enables workers to engage more meaningfully in strategic and analytical tasks, which can increase job satisfaction and overall productivity. Mining companies that adopt DT initiatives often observe that employees become more engaged when their roles are aligned with innovative, higher-level functions, which encourages a stronger commitment to their work and supports improved performance outcomes (Bakker & Demerouti, 2017).

This mediating effect of EE emphasises its importance as a critical element for DT success. When employees are well-engaged, they experience higher job satisfaction, adaptability, and motivation, which, in turn, strengthens the impact of DT initiatives. Research supports the notion that EE amplifies the effect of DT on JP by enhancing cognitive, behavioural, and emotional engagement, allowing employees to take an active role in organisational change (Bakker & Albrecht, 2018; Kwon & Kim, 2020). Mining companies that have adopted comprehensive DT strategies have observed not only operational efficiencies but also a more engaged workforce that feels a stronger sense of purpose and contribution to organisational goals. This highlights the potential for industries like mining to leverage DT for both operational improvements and enhanced workforce engagement and performance (Bakker et al., 2020; Barnewold & Lottermoser, 2020).

These findings align theoretically with the job demands-resources (JD-R) model, where DT provides resources that alleviate job demands and enhance engagement and performance (Bakker & Demerouti, 2017). Through effective DT, organisations offer technologies that facilitate task management, foster adaptability, and support employee resilience. This is particularly valuable in industries like mining, where DT can reduce physical job demands, allowing employees to reallocate their cognitive efforts towards strategic and analytical functions. Consequently, the mediating role of EE maximises the impact of DT on performance, which encourages employees to adapt and fully leverage the resources offered by digitalisation (Akter et al., 2024).

In practice, organisations that prioritise EE within their DT strategies are likely to see greater returns on their technology investments. This approach calls for structured training programmes, regular employee recognition, and supportive leadership that collectively reinforce the positive effects of DT on engagement and JP. For organisations, especially within technology-intensive sectors such as mining, understanding and fostering this EE-DT relationship can lead to a more adaptive, productive workforce. Ultimately, these findings contribute to academic discourse by affirming that EE significantly mediates the DT-JP relationship, supporting theories that emphasise the role of EE in enhancing performance in digitally transforming workplaces (Bakker et al., 2020).

Organisations that harness the power of EE as a mediating factor in their DT initiatives not only enhance operational efficiency but also establish a resilient workforce ready to meet the demands of evolving industries. This strategic integration of EE within DT highlights a robust model for academic and practical frameworks, illustrating how DT's success hinges on active and engaged employees who contribute meaningfully to organisational goals.

Furthermore, accounting for demographic factors such as age, educational background, and experience level enhances the success of DT initiatives through engagement. Customising DT strategies to fit the unique characteristics of the workforce promotes engagement and a culture of inclusivity and innovation (Bakker & Albrecht, 2018; Schaufeli & Bakker, 2004). By recognising and adapting to these diverse needs, organisations create an environment that is more receptive to continuous change and sustained DT. This approach not only improves JP but also contributes to building a resilient and future-ready organisational culture. Recent literature reinforces effective DT achievement through a comprehensive approach that values EE, leverages workforce expertise, addresses resistance proactively, and incorporates demographic diversity. EE serves as the cornerstone of successful DT, enhancing JP and supporting long-term organisational growth (Buil et al., 2019; Albrecht et al., 2015). Through this integrated approach, organisations are better equipped to navigate the complexities of DT, ultimately fostering an environment that is both innovative and adaptable.

Therefore, this analysis emphasises the critical role of EE, specifically through CBE and EME, in enhancing the DT-JP relationship. These findings highlight the importance of embedding engagement strategies within DT efforts to achieve optimal JP outcomes. By bridging the gap between technological advancements and human-centric practices, organisations can realise sustained improvements in JP.

6.6.3 Correlations Between Constructs and Control Variables

The findings in Table 39 highlight significant associations between specific demographic characteristics and the constructs of engagement and JP. Age shows a modest positive correlation with EE at 0.105** (p = 0.008) and with JP at 0.087* (p = 0.026). These positive associations indicate that older employees may display slightly higher levels of emotional commitment and JP, potentially due to factors such as accumulated experience, organisational loyalty, or a deeper sense of belonging. The data reflects a workforce predominantly aged 30–49 (71%), representing mid-career professionals who are likely more responsive to engagement initiatives than their younger counterparts. This demographic often possesses the experience and skills to effectively incorporate new technologies into their roles, thereby improving both engagement and performance. These findings align with research by Bakker and Demerouti (2017) and Breevaart and Zacher (2019), which suggest that older employees frequently exhibit stable EE, positively influencing their work outcomes.

Table 39: Condensed Correlation Results Between Demographics Variables and Constructs

Kendall's Tau Correlations for Demographic Information					
		DT	EE	CBE	JP
Age	Correlation Coefficient	0,005	0,105**	0,069	0,087*
	Sig. (2-tailed)	0,906	0,008	0,084	0,026
	N	400	400	400	400
Educational Level	Correlation Coefficient	-0,012	-,109**	-,125**	-,105**
	Sig. (2-tailed)	0,756	0,006	0,002	0,007

Source: Author's illustration of results generated by SPSS

Education, on the other hand, displays a more complex relationship, revealing a negative correlation with CBE at -0.125** (p = 0.002) and slightly weaker negative associations with both EE at -0.109** (p = 0.005) and JP at -0.105** (p = 0.007). This inverse relationship may indicate that higher educational attainment does not necessarily equate to increased engagement or JP levels. The discrepancy may stem from differing job expectations, varied role demands, or a potential misalignment between highly educated individuals' aspirations and organisational goals. The study's population comprised a large percentage of postgraduates (41%) and specialists (36%), indicating a workforce equipped with advanced knowledge and skills, well-suited to leveraging DT and EE effectively. While research by Akter et al. (2024) suggests that employees with higher education levels are typically more engaged with complex tasks and display higher adaptability, contributing to stronger JP outcomes, this study's findings indicate a contrasting trend.

The lack of significant associations between job roles or work experience with any constructs suggests that these factors may be less influential in predicting engagement or performance in this context. This absence of correlation could imply that engagement strategies need to be universally accessible across job roles, without over-reliance on work experience or hierarchical position, to achieve optimal outcomes in both engagement and JP. Research by Akter et al. (2024) supports the notion that effective engagement strategies should focus on fostering inclusivity and adaptability, ensuring that all employees, regardless of their position or tenure, feel equally empowered to contribute to organisational goals.

6.6.4 Independent-Samples Kruskal-Wallis Test Results Summary

Table 40 presents the aggregated results from the Kruskal-Wallis test, assessing the distribution patterns of DT, EE, CBE, EME, and JP across different categories of age, educational level, job role, and work experience. The following sections provide detailed discussions of these results.

Table 40: The combined Kruskal-Wallis Test Results

	Age and Key Constructs		Educational Level and Key Constructs		Job Role and Key Constructs		Work Experience and Key Constructs	
	Null Hypothesis	Sig.[a,b]	Null Hypothesis	Sig.[a,b]	Null Hypothesis	Sig.[a,b]	Null Hypothesis	Sig.[a,b]
1	The distribution of DT is the same across categories of Age (in years).	0,099	The distribution of DT is the same across categories of Educational Level.	0,951	The distribution of DT is the same across categories of Job Role.	0,046	The distribution of DT is the same across categories of Work Experience.	0,550
2	The distribution of EE is the same across categories of Age (in years).	0,096	The distribution of EE is the same across categories of Educational Level.	0,032	The distribution of EE is the same across categories of Job Role.	0,014	The distribution of EE is the same across categories of Work Experience.	0,273
3	The distribution of CBE is the same across categories of Age (in years).	0,386	The distribution of CBE is the same across categories of Educational Level.	0,007	The distribution of CBE is the same across categories of Job Role.	0,007	The distribution of CBE is the same across categories of Work Experience.	0,130
4	The distribution of EME is the same across categories of Age (in years).	0,022	The distribution of EME is the same across categories of Educational Level.	0,029	The distribution of EME is the same across categories of Job Role.	0,015	The distribution of EME is the same across categories of Work Experience.	0,361
5	The distribution of JP is the same across categories of Age (in years).	0,053	The distribution of JP is the same across categories of Educational Level.	0,001	The distribution of JP is the same across categories of Job Role.	0,021	The distribution of JP is the same across categories of Work Experience.	0,525

Source: Author's illustration of results generated by SPSS

6.6.4.1 Association Between Age and Key Constructs

The findings in Table 40 suggest that constructs like DT, EE, CBE, and JP do not vary significantly across age groups, as indicated by p-values above 0.05. This implies that age does not significantly influence perceptions of DT or levels of engagement and performance, aligning with studies that have found these attributes to be relatively consistent across age demographics (Bakker et al., 2020; Kwon & Kim, 2020). For this study, the high proportion of employees aged 30–49 (71%), representing a predominantly mid-career workforce, is not likely to impact DT, EE, CBE, and JP outcomes. For organisations, this insight suggests that age may not be a critical factor when implementing DT initiatives or developing engagement strategies. Instead, it supports the idea of universal engagement practices that resonate across generational lines, ensuring inclusivity and effectiveness for diverse workforces.

However, the significant variation in EME across age groups ($p = 0.022$) reveals a detailed aspect, indicating that age might influence how emotionally connected employees feel toward their work. Pairwise comparisons, particularly between younger (18-29) and older age groups (50-59, over 60), suggest generational distinctions in emotional work engagement, possibly reflecting varying career priorities or personal values. Organisations may benefit from tailored engagement approaches, particularly for fostering EME among younger and older employees, a strategy supported by recent research on age-specific engagement differences (Kooij & Boon, 2018). These findings align with Kendall's Tau correlation, which found a weak significant association between age and EE, suggesting that age influences engagement.

6.6.4.2 Association Between Educational Level and Key Constructs

The analysis of educational level's association with key constructs reveals that while DT does not significantly vary across educational backgrounds ($p = 0.951$), educational diversity has an impact on engagement dimensions like the full EE construct and cognitive and behavioural engagement (CBE), both showing significant variations ($p = 0.032$ and $p = 0.007$, respectively). These findings imply that the large percentage of postgraduates (41%) and specialists (36%), a workforce with advanced knowledge and skills, well-suited to leveraging DT effectively does not directly affect the DT efforts. However, employees' educational backgrounds may shape their engagement experiences, especially in cognitive and behavioural aspects, aligning with studies showing that higher education enhances adaptive skills and openness to organisational initiatives (Bakker & de Vries, 2021).

The results indicate that JP varies significantly across educational levels ($p = 0.001$), suggesting that higher educational attainment might offer skills conducive to productivity and role satisfaction (Kooij & Boon, 2018). However, Kendall's Tau correlation between educational level and EE, CBE, and JP shows an inverse relationship, implying that increased education does not always correlate with higher engagement or JP. This outcome could reflect differing job expectations, role demands, or a potential misalignment with organisational objectives among highly educated employees (Kooij & Boon, 2018; Bakker et al., 2020).

Practically, these findings suggest that organisations should account for educational diversity when developing engagement and training initiatives, as employees' formal education levels might shape their responses to DT efforts (Bakker & de Vries, 2021). Theoretically, the results support the relevance of educational diversity in engagement research, underscoring the need for tailored interventions that address the varied expectations and contributions of employees with differing educational backgrounds (Kooij & Boon, 2018; Bakker et al., 2020).

6.6.4.3 Association Between Job Role and Key Constructs

The analysis highlights that job roles substantially impact engagement dimensions (EE, CBE, and EME) and JP, whereas perceptions of DT are consistent across roles. This finding suggests that EE through CBE and EME varies significantly by role, emphasising the importance of customised engagement strategies (Albrecht et al., 2015). For example, differences in CBE between specialists, senior managers, and administrative staff imply that tailored approaches focused on these engagement dimensions may enhance productivity and satisfaction within each role (Saks & Gruman, 2021). Such role-driven engagement differences reveal that one-size-fits-all engagement strategies may be less effective, underscoring the benefit of a targeted approach to foster commitment and improve performance.

Research increasingly shows that leveraging existing employee expertise enhances engagement and supports DT efforts. Recent studies underscore the benefits of involving employees in digital process improvements, drawing on the specialised insights they offer (Alobidyeen et al., 2022; Zomer et al., 2020). By actively involving employees in DT initiatives, organisations foster a sense of ownership and empowerment, enabling employees to align digital strategies closely with operational needs. Such involvement not only refines digital solutions for practical relevance but also drives greater engagement, as employees feel their contributions meaningfully shape DT goals and processes, enhancing both engagement and effectiveness.

From an academic perspective, the results build on research by Saks and Gruman (2021), who argue that engagement's impact on JP is contingent upon job-specific factors. The findings align with current theories suggesting that engagement and performance vary according to role-based responsibilities and influence, supporting the call for more targeted engagement approaches in organisational psychology (Albrecht et al., 2015; Saks & Gruman, 2021). These insights contribute to our understanding of engagement's role in driving performance, particularly within differentiated job contexts where tailored strategies are critical for sustaining long-term organisational effectiveness.

6.6.4.4 Association Between Work Experience and Key Constructs

The findings show that work experience does not significantly differentiate perceptions of DT, engagement, or JP across the constructs examined. With p-values above 0.05 for each construct (e.g., $p = 0.550$ for DT, $p = 0.273$ for EE, and $p = 0.525$ for JP), the findings suggest that work experience does not substantially influence employees' perceptions of DT, nor does it affect engagement or self-assessed performance levels. This stability suggests that work experience alone does not directly influence employee attitudes toward organisational change, such as DT initiatives or engagement strategies, aligning with research by Bakker and Albrecht (2018), who found that work experience does not inherently predict engagement levels.

From a practical standpoint, these insights imply that organisations can adopt uniform engagement and DT strategies across employee work experience groups without tailoring specifically by experience level. This approach can simplify policy implementation, focusing more on role-specific or demographic factors rather than work experience. Theoretically, this finding contributes to engagement literature by suggesting that, while age or educational level might impact perceptions of DT or engagement, work experience may not be a significant variable. Such results call for future research into the factors beyond experience that may influence engagement, particularly as companies integrate DT and seek to drive JP universally across experience levels, as noted by (Kooij & Boon, 2018). These findings add detail to workforce engagement research, suggesting that work experience may be less relevant than other demographics in predicting receptiveness to organisational change.

6.6.5 Hypothesis Testing Summary

These hypotheses testing findings suggest that DT positively impacts both engagement and performance, with EE playing a crucial mediating role. For organisations, these insights highlight the importance of tailoring DT initiatives and engagement strategies to accommodate varying levels of experience, educational backgrounds, and job specialisations within the workforce. By investing in targeted engagement initiatives that consider these factors, organisations can optimise the impact of DT, fostering a more engaged and high-performing workforce.

6.7 Results Analysis Chapter Conclusion

The results analysis chapter provides a comprehensive examination of the data, focusing on the reliability and validity of the measurement instruments, assumptions testing, descriptive statistics, and in-depth hypotheses testing. Beginning with reliability tests, high Cronbach's alpha values for each construct DT, EE, and JP confirm the internal consistency of the measurement instruments, ensuring accurate capturing of constructs. Following this, Pearson's correlation and Exploratory Factor Analysis (EFA) internal validity assessments confirmed that the items consistently measured their intended constructs, validating the coherence and appropriateness of the constructs in the study.

Assumptions testing for normality and homoscedasticity revealed non-normal distribution in the data, leading to the adoption of non-parametric tests for hypothesis analysis. Descriptive statistics explored demographic data and construct-level insights, revealing a predominantly mid-career sample with high levels of educational attainment and specialist roles, adding context to the subsequent analyses of DT, EE, and JP relationships.

The hypotheses testing section uncovered significant relationships across constructs. The DT and JP relationship positively correlated, indicating that DT initiatives can improve JP, providing practical insights for organisations seeking to optimise productivity through digital strategies. Furthermore, DT showed a strong positive association with EE, specifically in cognitive-behavioural and emotional engagement components, suggesting that DT has the potential to enhance employee commitment and motivation. This study supported EE's mediating role between DT and JP, reinforcing the theory that engaged employees are more likely to leverage DT effectively, leading to higher performance outcomes. These findings align with studies supporting EE as a vital factor in successful DT and productivity gains.

Finally, the Kruskal-Wallis test identified significant differences across demographic categories, emphasising the importance of customised approaches to DT and EE across various employee groups. These insights contribute both practically, by guiding organisations in implementing tailored DT strategies, and theoretically, by reinforcing the multidimensional impact of DT on engagement and performance, particularly within specialised fields like the mining sector.

7. Chapter 7: Conclusion and Recommendations

This chapter summarises the core conclusions from the research, specifically addressing the study's problem statement and its significance in examining DT within the South African mining sector. The study aimed to understand the impact of DT on EE and JP while providing insights and recommendations for management within the sector. This chapter discusses the theoretical implications, contributions to academic knowledge, recommendations for management and stakeholders, limitations of the study, and suggestions for future research.

7.1 Principal Theoretical Conclusions

The findings presented in Chapter 6 highlight the central role of DT, EE, and JP within the South African mining sector, illustrating how these factors interrelate to drive organisational outcomes. DT initiatives directly contribute to JP by enhancing operational efficiency and reducing errors, a critical advantage in the high-risk mining environment. DT supports real-time decision-making, optimises resource allocation, and streamlines workflows, aligning with theories that position DT as a lever for operational efficiency in resource-intensive industries (Bakker & Demerouti, 2017; Gregorio et al., 2020).

The study further underscores the mediating role of EE in maximising DT's benefits on JP, showing that highly engaged employees are more adaptable and responsive to digital innovations. Without strong engagement, digital technologies may fall short of their potential to improve performance. Findings suggest that DT enhances engagement by shifting employees' focus from repetitive tasks to value-added activities, empowering them with more meaningful and productive roles. This effect supports the Job Demands-Resources (JD-R) model, which posits that resources like digital technologies can enhance engagement and performance when effectively implemented (Akter et al., 2024). By cultivating an engaged workforce, companies can more effectively harness DT's benefits, thereby improving both productivity and employee satisfaction, essential elements for the sustainable growth of the sector (AlNuaimi et al., 2022).

Furthermore, the analysis reveals that cognitive-behavioural engagement (CBE) and emotional engagement (EME) are integral pathways through which DT positively influences JP. Cognitive engagement appears particularly influential in driving performance outcomes in settings enriched by digital technologies. By emphasising CBE and EME as critical engagement dimensions, this study expands the theoretical discourse on DT's role in enhancing performance within sectors characterised by high operational demands, affirming EE as a central mediator in the DT-JP relationship (Bakker & Demerouti, 2017; Kwon & Kim, 2020).

The significance of this research lies in its focus on the South African mining sector; a critical but challenging industry for the country's economy. This sector faces pressures from fluctuating commodity prices, regulatory demands, and environmental constraints, making DT a vital strategy for resilience and competitiveness. By integrating technologies like predictive analytics, data-driven decision-making, and automation, DT offers mining companies a path toward operational agility, cost reduction, and enhanced safety (Barnewold & Lottermoser, 2020; Zomer et al., 2020). Thus, DT is not merely a tool for improvement; it is an essential factor for improving employees' performance through engagement.

Therefore, the study's research questions align closely with its objectives, addressing how DT impacts JP in the mining industry, and how EE influences their relationship. By focusing on these interconnected areas, the study contributes valuable insights into the evolving dynamics of workplace engagement and productivity in response to technological advancements.

7.2 Research Academic Contribution

This study makes significant academic contributions by expanding the understanding of DT, EE, and JP within the unique context of the South African mining industry. Previous research has predominantly focused on the manufacturing and service sectors, leaving a gap in the literature specific to the mining sector, particularly in high-risk environments that pose unique operational challenges and safety concerns (AlNuaimi et al., 2022; Gruenhagen & Parker, 2020). By providing empirical insights tailored to this sector, this research addresses this gap, adding substantial value to the academic discourse on DT's impact on industries with complex operational demands.

This study advances the theoretical framework of DT's role in enhancing JP by establishing EE as a key mediator. Unlike much prior research that emphasises DT's direct influence on organisational efficiency, this study explores the mechanisms through which DT improves individual performance. The findings suggest that DT's advantages extend beyond efficiency gains; they also enhance employees' work experiences by fostering engagement, autonomy, and meaning in their roles. This aligns with the Job Demands-Resources (JD-R) model, which posits that digital resources, when deployed effectively, serve as job resources that alleviate task demands, thereby promoting EE and productivity (Bakker & Demerouti, 2017). This connection reinforces recent studies within high-demand sectors, where digital technologies have elevated JP by enabling increased engagement and facilitating employees' capacity to manage their roles with greater effectiveness (Chatterjee, Rana, et al., 2021).

Additionally, this research contributes to understanding how DT functions within a framework of holistic change management, particularly when technology intersects with employee-centric factors. By identifying EE as a central mediator in the DT-JP relationship, the study highlights that the success of DT initiatives depends significantly on the workforce's engagement levels and adaptability (Bakker & Demerouti, 2017; Kwon & Kim, 2020). This insight is particularly valuable for industries like mining, where safety, compliance, and adaptation to technological advancements are critical (Barnewold & Lottermoser, 2020). The study's findings emphasise that EE should be a core component of DT frameworks, adding to the discourse on organisational behaviour within high-risk industries and aligning with findings that underscore employee involvement as vital for successful DT implementation (Kooij & Boon, 2018).

The study also offers theoretical contributions that extend beyond the South African context, providing globally relevant insights. It demonstrates the importance of organisational agility and adaptability in digitally transforming sectors, suggesting that DT success requires not only technological integration but also a cultural shift towards innovation and resilience (Bakker & Demerouti, 2017; Albrecht et al., 2015). The study thus informs the broader discourse on DT's impact, showing that adaptable, engaged workforces are essential for realising DT's full potential. This framework offers valuable insights for other mining sectors worldwide that face similar challenges in balancing tradition with the demands of digital modernisation. Consequently, this study reinforces the importance of robust change management, agility, and a focus on EE as essential components in navigating digital disruption in organisational contexts, aligning with current research in organisational studies that emphasises these factors (Saks, 2019).

Therefore, this research enriches the academic literature by providing empirical data that extends existing theories on DT's role in high-risk industries, emphasising the essential role of EE as a mediator. Addressing the unique dynamics of the mining sector, it underscores the importance of EE and organisational adaptability in DT strategies, thereby offering a framework that can guide both theoretical exploration and practical applications across similar industrial contexts.

7.3 Recommendations for Management and Stakeholders

The findings from this study underscore several critical recommendations for management and stakeholders in the South African mining sector, highlighting the need for a strategic and holistic approach to DT. Given the substantial influence of DT on EE and JP, management needs to regard DT as more than just an operational improvement tool; it should also be a driver of workforce engagement.

Aligning DT initiatives with EE goals is crucial to maximising the effectiveness of digital technologies. Management should design DT strategies that align with organisational engagement objectives, thereby fostering a work environment that not only leverages technological advancements but also supports employee well-being and productivity (AlNuaimi et al., 2022). Additionally, an investment in comprehensive training and development is essential. As DT often requires new skill sets, organisations must implement robust training programmes that ensure employees are well-equipped to utilise digital technologies effectively. Regular skill development and ongoing support reduce resistance to change by instilling confidence in employees, thus fostering higher engagement levels (Saks, 2019).

Creating a supportive organisational culture that promotes collaboration, open communication, and psychological safety is vital for enhancing the outcomes of DT initiatives. A culture of support ensures that employees feel secure as they adapt to digital advancements, which in turn positively impacts emotional engagement and JP. By establishing a collaborative and inclusive environment, management can enable employees to more readily embrace new technologies, which supports both individual and organisational growth (Mollah et al., 2023; Kooij & Boon, 2018).

Furthermore, organisations should prioritise DT initiatives that directly enhance work quality by streamlining repetitive tasks and improving information flow. Technologies such as data analytics and automation can reduce cognitive strain by handling routine tasks, thereby allowing employees to concentrate on more meaningful responsibilities. This approach not only improves work quality but also fosters higher cognitive and behavioural engagement, which positively affects performance (Chatterjee, Rana, et al., 2021).

Continuous feedback and recognition are also essential in a digitally transforming environment. Structured feedback mechanisms that provide real-time performance insights, along with recognition for contributions, reinforce engagement by making employees feel valued. This practice aligns employees with the organisation's goals and maintains their motivation, which is essential for sustaining engagement in a changing technological landscape (Bakker & Demerouti, 2017; Albrecht et al., 2015).

In addition to internal practices, the findings highlight the importance of management undertaking a proactive approach to digital integration. Cultivating a culture of innovation is essential, as it encourages employees to experiment with and adopt new technologies. This includes providing continuous training and resources to enhance digital literacy, enabling employees to effectively engage with digital technologies. Organisations that foster a culture of learning and innovation tend to significantly outperform those that do not (Gruenhagen & Parker, 2020).

Investment in technology infrastructure is another priority. A thorough needs assessment should identify areas where digital technologies can create the most significant impact. These investments must go beyond hardware upgrades and include software solutions that enhance data analytics and decision-making capabilities, ensuring that the organisation remains agile and responsive in a competitive market (Deloitte, 2022).

Engaging in strategic collaborations with technology providers, research institutions, and academic organisations can further enhance the innovative capacity of mining companies. Partnerships foster knowledge transfer and skill development, preparing the workforce for an evolving technological landscape. Collaborative innovation is a crucial driver of competitive advantage, particularly in high-demand industries like mining (AlNuaimi et al., 2022; Zomer et al., 2020).

Data-driven decision-making is fundamental to optimising DT outcomes. Implementing policies that prioritise data collection, analysis, and utilisation helps organisations make informed decisions that enhance operational efficiencies, forecast accuracy, and risk management. Leveraging advanced analytics provides critical insights that can guide both strategic directions and day-to-day operational choices, thereby strengthening the organisation's performance (Correani et al., 2020; Onifade et al., 2023).

Finally, integrating sustainability into core business strategies is essential in today's mining industry, given increasing regulatory and societal expectations. By embedding sustainability principles within DT initiatives, companies can position themselves as responsible corporate citizens committed to environmental stewardship. This focus on sustainability not only improves brand reputation but also confers a competitive advantage in a market that increasingly values environmental responsibility (Barnewold & Lottermoser, 2020; Deloitte, 2024).

Therefore, management's role in effective DT implementation extends beyond mere technology adoption; it involves fostering an engaged, adaptable workforce capable of leveraging digital technologies for organisational success. By addressing these strategic factors, mining companies can create a positive feedback loop in which DT initiatives boost EE, thereby enhancing JP and contributing to overall organisational effectiveness (Bakker & Albrecht, 2018; Akter et al., 2024).

7.4 Imitations of the Research

Despite offering valuable insights into the relationship between DT, EE, and JP within the South African mining sector, this study proposes several limitations for consideration. Firstly, the geographical focus on South Africa restricts the generalisability of the findings to other regions or industries. While the South African mining sector provides valuable context-specific insights, the unique operational demands, regulatory frameworks, and technological infrastructures of other sectors or countries may differ significantly. Future research could address this limitation by conducting comparative studies across various industries and geographic locations to better understand how EE mediates the DT-JP relationship in different contexts (AlNuaimi et al., 2022; Barnewold & Lottermoser, 2020).

Another limitation is the reliance on cross-sectional data, which constrains the ability to establish causal relationships between DT, EE, and JP. While the study observed significant correlations, a longitudinal design would offer a more robust view of how DT initiatives influence EE and JP over time. This approach could provide deeper insights into the long-term trends and effects of DT on EE and performance (Bakker & Albrecht, 2018; Kwon & Kim, 2020).

Furthermore, the study's sample size, confined to specific mining companies, may limit the representativeness of the findings. Some participants may have experienced survey fatigue, which could have affected the accuracy of their responses. Self-reported measures for EE, JP, and DT could also introduce social desirability bias, where respondents may rate their engagement or performance more favourably, especially given the organisational emphasis on DT. To mitigate these issues, future studies could incorporate objective performance data or adopt a mixed-methods approach that combines quantitative and qualitative insights to provide a more comprehensive understanding of the DT-EE-JP relationship (Creswell & Creswell, 2020).

Finally, the rapid pace of advancements in digital technologies means that the findings may quickly become outdated. As DT continues to evolve, ongoing research is essential to keep pace with these changes and assess their implications for industries like mining. Longitudinal studies that track the progress of digital initiatives and their impact on EE and performance will ensure that research remains relevant and reflective of the current technological landscape (Albrecht et al., 2015; Zomer et al., 2020).

Therefore, by addressing these limitations, future research can provide more comprehensive and applicable insights into the role of EE in the relationship between DT and JP, offering valuable guidance for both academia and industry.

7.5 Suggestions for Future Research

Building on the limitations outlined, the study identified several areas for future research to enhance understanding of the impact of DT on EE and JP, particularly within the mining sector.

A key direction for future research is the exploration of comparative studies across sectors. While this study focused on the South African mining sector, the impact of DT could vary significantly across different industries. Comparative studies across diverse sectors, such as manufacturing or healthcare, would allow for a broader understanding of how EE mediates the relationship between DT and JP in different organisational contexts. Such studies could reveal sector-specific challenges and opportunities, providing insights into best practices for implementing digital strategies in varied operational environments (AlNuaimi et al., 2022; Bresciani et al., 2021).

Additionally, the study recommends a longitudinal approach to studying the effects of DT on EE and JP for future research. This would provide valuable insights into the long-term impact of DT, as sustained engagement with digital technologies may influence JP over time. Longitudinal studies would capture how these relationships evolve, providing robust evidence of causality and revealing long-term trends that cross-sectional studies cannot (Bakker & Demerouti, 2017; Trenerry et al., 2021).

Furthermore, future research could delve deeper into additional mediating factors beyond EE, such as organisational culture, adaptability, and innovation climate. These factors may offer a more comprehensive understanding of the DT-JP relationship. Investigating how organisational culture and climate influence EE and performance in the context of DT could provide important insights into fostering a supportive environment for successful DT initiatives (Saks & Gruman, 2021; Lazarenko et al., 2021).

The exploration of the impact of specific digital technologies within the mining sector represents another valuable avenue for future research. For instance, examining the effects of technologies such as AI, IoT, and predictive analytics could provide more detailed insights into which technologies offer the most significant performance benefits. This would allow for a better understanding of the specific digital technologies that drive engagement and performance improvements in mining operations (Barnewold & Lottermoser, 2020; Zomer et al., 2020).

Further research should also consider the employee perspective on DT, particularly in terms of resistance factors and the support employees need to transition smoothly. Understanding employees' psychological and cultural responses to new technologies can inform strategies to manage resistance and improve acceptance. This could be particularly relevant in the mining sector, where new digital technologies often require substantial shifts in employee behaviour and organisational practices (Breevaart & Zacher, 2019). Investigating these perspectives would offer valuable guidance for management in designing supportive interventions that facilitate smoother transitions and maximise the effectiveness of DT efforts.

Lastly, employing a mixed-methods approach could enrich the understanding of the DT-EE-JP relationship. Combining quantitative surveys with qualitative insights from interviews or focus groups would provide a more comprehensive view of how DT influences EE and JP. Qualitative data would allow researchers to capture the deeper perspectives and experiences of employees, offering valuable context to support quantitative findings (Saunders et al., 2019).

Therefore, future research should focus on these recommended areas to further explore the implications of DT for the mining sector and beyond. By aligning organisational strategies with emerging technologies, firms can not only enhance their competitiveness and sustainability but also better adapt to future challenges. The insights gained from such research will support the ongoing evolution of DT efforts and foster more innovative and inclusive approaches to mining operations.

7.6 Research Study Final Conclusions

In conclusion, this study provides meaningful insights into the relationship between DT, EE, and JP within the South African mining sector. The findings reveal that DT positively impacts JP, particularly when supported by a strong engagement culture. The theoretical contributions of this study advance the understanding of DT within high-risk industries, while the practical recommendations offer a roadmap for mining companies aiming to leverage digital technologies effectively.

The research underscores the importance of EE as a mediator in the DT process, highlighting that successful DT implementation requires management commitment to fostering a supportive and engaged workforce. Despite its limitations, this study lays the groundwork for future research that could broaden the understanding of DT in complex and dynamic industry environments.

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9. Appendices

9.1 Appendix 1 – Questionnaire for the Research Study

9.1.1 Survey Introduction Letter

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I am a student at the University of Pretoria's Gordon Institute of Business Science and currently conducting research on **"The effect of digital transformation on job performance, mediated or moderated by employee engagement"**. The aim is to determine if digital transformation has an impact on job performance and whether employee engagement influences the relationship between digital transformation and employee engagement. To that end, you are asked to complete a survey relating to my topic. The survey questions should take no more than 5 to 10 minutes to complete. Your participation is voluntary, and you can withdraw at any time without penalty. Your participation is anonymous and only aggregated data will be reported. By completing the survey, you indicate that you voluntarily participate in this research. If you have any concerns, please contact my supervisor or me. Our details are provided below.

Themba Magubane
Researcher
e-mail: 23023229@mygibs.co.za

Hugh Myres
Supervisor
e-mail: myresh@gibs.co.za

Please indicate if you agree to continue with the survey

Yes

No

9.1.2 Survey Control Questions

Table 41: Survey Control Questions

Control Type	Control Question	Answer Selection	
Target population - Mining Industry employees	Are you currently working in the mining industry in South Africa?	Yes	If not, please specify your industry and country employment
Target population - Knowledge workers	Do you use a computer most of the time when you execute your daily duties?	Yes	No

Source: Author's illustration

9.1.3 Demographics

Table 42: Demographics Questions

Category	Survey Question	Answer Selection					
Age	What is your age group?	18-29 years old	30-39 years old	40-49 years old	50-29 years old	More than 60 years old	
Education	What is your highest qualification?	Matric/Grade 12	Diploma	Bachelor's degree	Post graduate degree		
Job Role	What profession aligns the most with your job?	Administration	Specialist	Manager	Senior Manager	Executive	
Work Experience	How many years of employment in your current role? Please do not include your previous work experience.	Less than 1 year	1-5 years	6-10 years	11-15 years	16-20 years	More than 20 years

Source: Author's illustration

9.1.4 Digital Transformation Measurement Instrument

Table 43: DT Measurement Instrument

Digital Transformation Measurement Instrument						
Question No	**Construct Item Statement**	**Strongly agree**	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
Q1	In my organisation, we aim to digitalise everything that can be digitalised.					
Q2	In my organisation, we collect large amounts of data from different sources.					
Q3	In my organisation, we aim to increase connectivity between different business processes through digitisation.					
Q4	In my organisation, we aim to enhance customer interface through digitalisation.					
Q5	In my organisation, we aim to achieve information exchange through digitalisation.					

Source: Author's illustration based on AlNuaimi et al., (2022) and Nasiri et al., (2020)

Note: The researcher adjusted questions 2, 3 and 4 in the survey questionnaire for clarity, as shown below:

Original question 3: In my organisation, we aim to create more robust networking with digital technologies between the different business processes.

Original question 4: In my organisation, we aim to enhance an efficient customer interface with digitality.

Original question 4: In my organisation, we aim at achieving information exchange with digitality.

9.1.5 Employee Engagement Measurement Instrument

Table 44: EE Measurement Instrument

Employment Engagement Measurement Instrument						
Question No	**Construct Item Statement**	**Strongly agree**	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
Q6	I am really too focused when I am working.					
Q7	I concentrate on my job when I am at work.					
Q8	I give my job responsibility a lot of attention.					
Q9	At work, I am focused on my job.					
Q10	I really push myself to work beyond what is expected of me.					
Q11	I am willing to put in extra effort without being asked.					
Q12	I often go above what is expected of me to help my team be successful.					
Q13	I work harder that expected to help my company be successful.					
Q14	Working at my current organisation has a great deal of personal meaning to me.					
Q15	I feel a strong sense of belonging to my job.					
Q16	I believe in the mission and purpose of my company.					
Q17	I care about the future of my company.					

Source: Author's illustration based on Shuck et al., (2017)

9.1.6 Job Performance Measurement Instrument

Table 45: Job Performance Measurement Instrument

Job Performance Measurement Instrument						
Question No	**Construct Item Statement**	**Strongly agree**	**Agree**	**Neutral**	**Disagree**	**Strongly Disagree**
Q18	I manage to plan my work so that it is done on time.					
Q19	My planning is optimal.					
Q20	I keep in mind the results that I have to achieve in my work.					
Q21	I am able to separate main issues from side issues at work.					
Q22	I am able to perform my work well with minimal time and effort.					
Q23	I take on extra responsibilities.					
Q24	I start new tasks myself, when my old ones are finished.					
Q25	I take on challenging work tasks, when available.					
Q26	I work at keeping my job knowledge up-to-date.					
Q27	I work at keeping my job skills up-to-date.					
Q28	I come up with creative solutions to new problems.					
Q29	I keep looking for new challenges in my job.					
Q30	I to actively participate in work meetings.					

Source: Author's illustration based on Koopmans et al., (2014).

9.2 Appendix 2 – Data Coding

9.2.1 Likert Scale Coding

Table 46: Numerical codes assigned to the Likert Measurement Scale

Item Label	Code	Item Label	Code	Item Label	Code	Item Label	Code	Item Label	Code
Strongly disagree	1	Somwhat disagree	2	Neutral	3	Somewhat agree	4	Strongly agree	5

Source: Author's illustration

9.2.2 Demographic Data Coding.

Table 47: Numerical Codes Assigned for Categorising Demographic Data

Item Label	Question	Possible Answers	Code
Age	Which age group do you belong to?	18-29 years old	1
		30-39 years old	2
		40-49 years old	3
		50-59 years old	4
		More than 60 years	5
Education	What is your highest qualification?	Matric/Grade 12	1
		Diploma	2
		Bachelor's degree	3
		Post graduate degree	4
Job Role	What profession aligns the most with your job?	Administration	1
		Specialist	2
		Manager	3
		Senior Manager	4
		Executive	5
Work Experience	How many years of employment in your current role? Please do not include your previous work experience.	Less than 1 year	1
		1-5 years	2
		6-10 years	3
		11-15 years	4
		16-20 years	5
		More than 20 years	6

Source: Author's illustration

9.2.3 Digital Transformation Data Coding

Table 48: DT Data Coding

Construct Item Statement	Coding Label
In my organisation, we aim to digitalise everything that can be digitalised.	DT1
In my organisation, we collect large amounts of data from different sources.	DT2
In my organisation, we aim to increase connectivity between different business processes through digitisation.	DT3
In my organisation, we aim to enhance customer interface through digitalisation.	DT4
In my organisation, we aim to achieve information exchange through digitalisation.	DT5

Source: Author's illustration based on AlNuaimi et al., (2022) and Nasiri et al., (2020)

9.2.4 Employee Engagement Data Coding

Table 49: EE Data Coding

Construct Item Statement	Coding Label	Construct Item Statement	Coding Label
I am really too focused when I am working.	CE1	I often go above what is expected of me to help my team be successful.	BE3
I concentrate on my job when I am at work.	CE2	I work harder that expected to help my company be successful.	BE4
I give my job responsibility a lot of attention.	CE3	Working at my current organisation has a great deal of personal meaning to me.	EME1
At work, I am focused on my job.	CE4	I feel a strong sense of belonging to my job.	EME2
I really push myself to work beyond what is expected of me.	BE1	I believe in the mission and purpose of my company.	EME3
I am willing to put in extra effort without being asked.	BE2	I care about the future of my company.	EME4

Source: Author's illustration based on Shuck et al., (2017)

9.2.5 Job Performance Data Coding

Table 50: JP Data Coding

Job Performance Construct Item Statement	Coding Label
I manage to plan my work so that it is done on time.	TP1
My planning is optimal.	TP2
I keep in mind the results that I have to achieve in my work.	TP3
I am able to separate main issues from side issues at work.	TP4
I am able to perform my work well with minimal time and effort.	TP5
I take on extra responsibilities.	CP1
I start new tasks myself, when my old ones are finished.	CP2
I take on challenging work tasks, when available.	CP3
I work at keeping my job knowledge up-to-date.	CP4
I work at keeping my job skills up-to-date.	CP5
I come up with creative solutions to new problems.	CP6
I keep looking for new challenges in my job.	CP7
I to actively participate in work meetings.	CP8

Source: Author's illustration based on Koopmans et al., (2014)

9.3 Appendix 3 – Measuring Instruments Reliability Tests

9.3.1 Digital Transformation Measuring Instrument Reliability Test

Table 51: DT Measuring Instrument Reliability Test Results (Total Statistics)

DT - Item-Total Statistics				
Item Code	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
DT1	16,6	12,8	0,71	0,865
DT2	16,4	13,5	0,60	0,889
DT3	16,5	12,6	0,77	0,851
DT4	16,7	12,7	0,74	0,859
DT5	16,4	12,5	0,81	0,844

Source: Author's own illustration of results generated by SPSS

9.3.2 Employee Engagement Measuring Instrument Reliability Test

Table 52: EE Measuring Instrument Reliability Test Results (Total Statistics)

EE - Item-Total Statistics				
Item Code	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
CE1	48,6	76,6	0,649	0,956
CE2	48,3	75,5	0,775	0,952
CE3	48,1	75,3	0,864	0,949
CE4	48,3	75,3	0,801	0,951
EE1	48,5	75,9	0,706	0,954
EE2	48,8	75,6	0,659	0,956
EE3	48,5	75,2	0,727	0,953
EE4	48,2	74,6	0,843	0,950
BE1	48,3	74,3	0,857	0,949
BE2	48,2	74,4	0,871	0,949
BE3	48,2	75,2	0,856	0,949
BE4	48,4	74,8	0,827	0,950

Source: Author's own illustration of results generated by SPSS

9.3.3 Job Performance Measuring Instrument Reliability Test

Table 53: JP Measuring Instrument Reliability Test Results (Total Statistics)

DT - Item-Total Statistics				
Item Code	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
DT1	16,57	12,812	0,71	0,865
DT2	16,40	13,544	0,60	0,889
DT3	16,52	12,581	0,77	0,851
DT4	16,68	12,716	0,74	0,859
DT5	16,42	12,494	0,81	0,844

Source: Author's illustration of results generated by SPSS

9.4 Appendix 4 – Construct Validity Matrices

Table 54: Digital Transformation – Pearson's Correlation Matrix

Digital Transformation Construct Items Correlations Matrix							
		DT1	DT2	DT3	DT4	DT5	DT_TOT
DT1	Pearson Correlation	1	,524**	,649**	,603**	,629**	,822**
	Sig. (2-tailed)		<0,001	<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400
DT2	Pearson Correlation	,524**	1	,511**	,495**	,568**	,748**
	Sig. (2-tailed)	<0,001		<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400
DT3	Pearson Correlation	,649**	,511**	1	,666**	,745**	,859**
	Sig. (2-tailed)	<0,001	<0,001		<0,001	<0,001	<0,001
	N	400	400	400	400	400	400
DT4	Pearson Correlation	,603**	,495**	,666**	1	,719**	,839**
	Sig. (2-tailed)	<0,001	<0,001	<0,001		<0,001	<0,001
	N	400	400	400	400	400	400
DT5	Pearson Correlation	,629**	,568**	,745**	,719**	1	,880**
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001		<0,001
	N	400	400	400	400	400	400
DT_TOT	Pearson Correlation	,822**	,748**	,859**	,839**	,880**	1
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001	
	N	400	400	400	400	400	400

**. Correlation is significant at the 0.01 level (2-tailed).

Source: Author's illustration of results generated by SPSS

Table 55: Employee Engagement – Pearson's Correlation Matrix

Employee Engagement Construct Items Correlations Matrix														
		CE1	CE2	CE3	CE4	EME1	EME2	EME3	EME4	BE1	BE2	BE3	BE4	EE_TOT
CE1	Pearson Correlation	1	,658**	,620**	,598**	,462**	,412**	,451**	,531**	,580**	,566**	,557**	,555**	,709**
	Sig. (2-tailed)		<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400
CE2	Pearson Correlation	,658**	1	,812**	,826**	,460**	,440**	,489**	,646**	,701**	,711**	,693**	,641**	,814**
	Sig. (2-tailed)	<0,001		<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400
CE3	Pearson Correlation	,620**	,812**	1	,812**	,585**	,506**	,602**	,754**	,775**	,790**	,805**	,752**	,886**
	Sig. (2-tailed)	<0,001	<0,001		<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400
CE4	Pearson Correlation	,598**	,826**	,812**	1	,551**	,497**	,512**	,658**	,703**	,725**	,728**	,682**	,836**
	Sig. (2-tailed)	<0,001	<0,001	<0,001		<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400
EME1	Pearson Correlation	,462**	,460**	,585**	,551**	1	,709**	,613**	,687**	,610**	,590**	,570**	,582**	,756**
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001		<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400
EME2	Pearson Correlation	,412**	,440**	,506**	,497**	,709**	1	,640**	,626**	,543**	,574**	,535**	,550**	,721**
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001		<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400
EME3	Pearson Correlation	,451**	,489**	,602**	,512**	,613**	,640**	1	,754**	,625**	,663**	,640**	,627**	,775**
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001		<0,001	<0,001	<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400
EME4	Pearson Correlation	,531**	,646**	,754**	,658**	,687**	,626**	,754**	1	,760**	,758**	,742**	,680**	,871**
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001		<0,001	<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400
BE1	Pearson Correlation	,580**	,701**	,775**	,703**	,610**	,543**	,625**	,760**	1	,853**	,811**	,785**	,882**
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001		<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400
BE2	Pearson Correlation	,566**	,711**	,790**	,725**	,590**	,574**	,663**	,758**	,853**	1	,821**	,807**	,894**
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001		<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400
BE3	Pearson Correlation	,557**	,693**	,805**	,728**	,570**	,535**	,640**	,742**	,811**	,821**	1	,838**	,879**
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001		<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400
BE4	Pearson Correlation	,555**	,641**	,752**	,682**	,582**	,550**	,627**	,680**	,785**	,807**	,838**	1	,855**
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001		<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400
EE_TOT	Pearson Correlation	,709**	,814**	,886**	,836**	,756**	,721**	,775**	,871**	,882**	,894**	,879**	,855**	1
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	
	N	400	400	400	400	400	400	400	400	400	400	400	400	400

**. Correlation is significant at the 0.01 level (2-tailed).

Source: Author's illustration of results generated by SPSS

Table 56: Job Performance – Pearson's Correlation Matrix

Job Performance Construct Items Correlations Matrix															
		TP1	TP2	TP3	TP4	TP5	CP1	CP2	CP3	CP4	CP5	CP6	CP7	CP8	CP_TOT
TP1	Pearson Correlation	1	,767**	,727**	,640**	,570**	,544**	,623**	,621**	,650**	,661**	,676**	,541**	,586**	,750**
	Sig. (2-tailed)		<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400	400
TP2	Pearson Correlation	,767**	1	,630**	,597**	,547**	,512**	,552**	,544**	,587**	,617**	,602**	,522**	,491**	,675**
	Sig. (2-tailed)	<0,001		<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400	400
TP3	Pearson Correlation	,727**	,630**	1	,674**	,512**	,611**	,604**	,676**	,680**	,688**	,660**	,597**	,605**	,782**
	Sig. (2-tailed)	<0,001	<0,001		<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400	400
TP4	Pearson Correlation	,640**	,597**	,674**	1	,613**	,549**	,493**	,573**	,581**	,608**	,609**	,529**	,518**	,680**
	Sig. (2-tailed)	0,000	0,000	0,000		0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000	0,000
	N	400	400	400	400	400	400	400	400	400	400	400	400	400	400
TP5	Pearson Correlation	,570**	,547**	,512**	,613**	1	,485**	,495**	,497**	,500**	,535**	,544**	,534**	,452**	,617**
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001		<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400	400
CP1	Pearson Correlation	,544**	,512**	,611**	,549**	,485**	1	,558**	,676**	,596**	,555**	,614**	,559**	,549**	,782**
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001		<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400	400
CP2	Pearson Correlation	,623**	,552**	,604**	,493**	,495**	,558**	1	,655**	,576**	,587**	,577**	,493**	,528**	,767**
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001		<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400	400
CP3	Pearson Correlation	,621**	,544**	,676**	,573**	,497**	,676**	,655**	1	,730**	,688**	,691**	,662**	,623**	,872**
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001		<0,001	<0,001	<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400	400
CP4	Pearson Correlation	,650**	,587**	,680**	,581**	,500**	,596**	,576**	,730**	1	,854**	,681**	,622**	,587**	,859**
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001		<0,001	<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400	400
CP5	Pearson Correlation	,661**	,617**	,688**	,608**	,535**	,555**	,587**	,688**	,854**	1	,684**	,647**	,566**	,849**
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001		<0,001	<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400	400
CP6	Pearson Correlation	,676**	,602**	,660**	,609**	,544**	,614**	,577**	,691**	,681**	,684**	1	,684**	,617**	,844**
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001		<0,001	<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400	400
CP7	Pearson Correlation	,541**	,522**	,597**	,529**	,534**	,559**	,493**	,662**	,622**	,647**	,684**	1	,609**	,802**
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001		<0,001	<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400	400
CP8	Pearson Correlation	,586**	,491**	,605**	,518**	,452**	,549**	,528**	,623**	,587**	,566**	,617**	,609**	1	,774**
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001		<0,001
	N	400	400	400	400	400	400	400	400	400	400	400	400	400	400
CP_TOT	Pearson Correlation	,750**	,675**	,782**	,680**	,617**	,782**	,767**	,872**	,859**	,849**	,844**	,802**	,774**	1
	Sig. (2-tailed)	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	<0,001	
	N	400	400	400	400	400	400	400	400	400	400	400	400	400	400

**. Correlation is significant at the 0.01 level (2-tailed).

Source: Author's illustration of results generated by SPSS

9.5 Appendix 5 – Control Variables and Constructs Associations

9.5.1 Age and EME Association: Pairwise Comparison

Table 57: Kruskal-Wallis Test Results: Age – EME Association

Pairwise Comparisons of Age and EME					
Sample 1-Sample 2	**Test Statistic**	**Std. Error**	**Std. Test Statistic**	**Sig.**	**Adj. Sig.[a]**
18-29 years old-30-39 years old	-13,391	19,871	-0,674	0,500	1,000
18-29 years old-40-49 years old	-28,346	20,285	-1,397	0,162	1,000
18-29 years old-50-59 years old	-54,647	22,566	-2,422	0,015	0,154
18-29 years old-More than 60 years old	-89,139	39,906	-2,234	0,026	0,255
30-39 years old-40-49 years old	-14,955	13,485	-1,109	0,267	1,000
30-39 years old-50-59 years old	-41,256	16,720	-2,467	0,014	0,136
30-39 years old-More than 60 years old	-75,748	36,917	-2,052	0,040	0,402
40-49 years old-50-59 years old	-26,301	17,211	-1,528	0,126	1,000
40-49 years old-More than 60 years old	-60,793	37,141	-1,637	0,102	1,000
50-59 years old-More than 60 years old	-34,492	38,434	-0,897	0,369	1,000

Source: Author's illustration of results generated by SPSS

9.5.2 Educational Level and EE Association: Pairwise Comparison

Table 58: Kruskal-Wallis Test Results: Educational Level – EE Association

Pairwise Comparisons of Educational Level and EE					
Sample 1-Sample 2	**Test Statistic**	**Std. Error**	**Std. Test Statistic**	**Sig.**	**Adj. Sig.a**
Post Graduate Degree-Bachelors Degree	8,690	14,032	0,619	0,536	1,000
Post Graduate Degree-Diploma	39,589	15,260	2,594	0,009	0,057
Post Graduate Degree-Matric/Grade 12	39,931	21,165	1,887	0,059	0,355
Bachelors Degree-Diploma	30,899	16,361	1,889	0,059	0,354
Bachelors Degree-Matric/Grade 12	31,241	21,972	1,422	0,155	0,930
Diploma-Matric/Grade 12	0,342	22,776	0,015	0,988	1,000

Source: Author's illustration of results generated by SPSS

9.5.3 Educational Level and CBE Association: Pairwise Comparison

Table 59: Kruskal-Wallis Test Results: Educational Level – CBE Association

Pairwise Comparisons of Educational Level and CBE

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
Post Graduate Degree-Bachelors Degree	3,858	13,930	0,277	0,782	1,000
Post Graduate Degree-Diploma	42,157	15,149	2,783	0,005	0,032
Post Graduate Degree-Matric/Grade 12	49,334	21,011	2,348	0,019	0,113
Bachelors Degree-Diploma	38,299	16,242	2,358	0,018	0,110
Bachelors Degree-Matric/Grade 12	45,476	21,812	2,085	0,037	0,222
Diploma-Matric/Grade 12	7,177	22,610	0,317	0,751	1,000

Source: Author's illustration of results generated by SPSS

9.5.4 Educational Level and JP Association: Pairwise Comparison

Table 60: Kruskal-Wallis Test Results: Educational Level – JP Association

Pairwise Comparisons of Educational Level and JP

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.a
Bachelors Degree-Post Graduate Degree	-10,396	14,068	-0,739	0,460	1,000
Bachelors Degree-Matric/Grade 12	39,938	22,028	1,813	0,070	0,419
Bachelors Degree-Diploma	59,943	16,403	3,654	<0,001	0,002
Post Graduate Degree-Matric/Grade 12	29,542	21,219	1,392	0,164	0,983
Post Graduate Degree-Diploma	49,547	15,299	3,239	0,001	0,007
Matric/Grade 12-Diploma	-20,005	22,834	-0,876	0,381	1,000

Source: Author's illustration of results generated by SPSS

9.5.5 Job Role and EE Association: Pairwise Comparison

Table 61: Kruskal-Wallis Test Results: Job Role – EE Association

Pairwise Comparisons of Job Role and EE					
Sample 1-Sample 2	**Test Statistic**	**Std. Error**	**Std. Test Statistic**	**Sig.**	**Adj. Sig.a**
Specialist-Manager	-12,32	14,65	-0,841	0,400	1,000
Specialist-Senior Manager	-44,45	19,78	-2,247	0,025	0,246
Specialist-Administration	46,41	15,76	2,945	0,003	0,032
Specialist-Executive	-48,11	27,41	-1,755	0,079	0,793
Manager-Senior Manager	-32,13	20,58	-1,561	0,119	1,000
Manager-Administration	34,09	16,75	2,034	0,042	0,419
Manager-Executive	-35,79	28,00	-1,278	0,201	1,000
Senior Manager-Administration	1,96	21,39	0,092	0,927	1,000
Senior Manager-Executive	-3,66	30,99	-0,118	0,906	1,000
Administration-Executive	-1,70	28,60	-0,060	0,952	1,000

Source: Author's illustration of results generated by SPSS

9.5.6 Job Role and CBE Association: Pairwise Comparison

Table 62: Kruskal-Wallis Test Results: Job Role – CBE Association

Pairwise Comparisons of Job Role and CBE					
Sample 1-Sample 2	**Test Statistic**	**Std. Error**	**Std. Test Statistic**	**Sig.**	**Adj. Sig.a**
Specialist-Manager	-6,46	14,54	-0,444	0,657	1,000
Specialist-Executive	-17,98	27,22	-0,661	0,509	1,000
Specialist-Senior Manager	-33,68	19,64	-1,715	0,086	0,863
Specialist-Administration	54,53	15,64	3,486	<0,001	0,005
Manager-Executive	-11,53	27,79	-0,415	0,678	1,000
Manager-Senior Manager	-27,23	20,43	-1,332	0,183	1,000
Manager-Administration	48,08	16,63	2,891	0,004	0,038
Executive-Senior Manager	15,70	30,77	0,510	0,610	1,000
Executive-Administration	36,55	28,39	1,288	0,198	1,000
Senior Manager-Administration	20,85	21,23	0,982	0,326	1,000

Source: Author's illustration of results generated by SPSS

9.5.7 Job Role and EME Association: Pairwise Comparison

Table 63: Kruskal-Wallis Test Results: Job Role – EME Association

Pairwise Comparisons of Job Role and EME					
Sample 1-Sample 2	**Test Statistic**	**Std. Error**	**Std. Test Statistic**	**Sig.**	**Adj. Sig.a**
Specialist-Manager	-7,81	14,42	-0,542	0,588	1,000
Specialist-Administration	26,18	15,52	1,688	0,091	0,915
Specialist-Senior Manager	-49,24	19,48	-2,528	0,011	0,115
Specialist-Executive	-69,16	26,99	-2,563	0,010	0,104
Manager-Administration	18,37	16,49	1,114	0,265	1,000
Manager-Senior Manager	-41,42	20,26	-2,044	0,041	0,409
Manager-Executive	-61,35	27,56	-2,226	0,026	0,260
Administration-Senior Manager	-23,05	21,06	-1,095	0,274	1,000
Administration-Executive	-42,98	28,15	-1,527	0,127	1,000
Senior Manager-Executive	-19,93	30,51	-0,653	0,514	1,000

Source: Author's illustration of results generated by SPSS

9.5.8 Job Role and JP Association: Pairwise Comparison

Table 64: Kruskal-Wallis Test Results: Job Role – JP Association

Pairwise Comparisons of Job Role and JP					
Sample 1-Sample 2	**Test Statistic**	**Std. Error**	**Std. Test Statistic**	**Sig.**	**Adj. Sig.a**
Specialist-Executive	-5,67	27,48	-0,206	0,837	1,000
Specialist-Manager	-15,73	14,69	-1,071	0,284	1,000
Specialist-Senior Manager	-37,64	19,83	-1,898	0,058	0,577
Specialist-Administration	50,05	15,80	3,168	0,002	0,015
Executive-Manager	10,06	28,07	0,358	0,720	1,000
Executive-Senior Manager	31,98	31,07	1,029	0,303	1,000
Executive-Administration	44,39	28,67	1,548	0,122	1,000
Manager-Senior Manager	-21,92	20,64	-1,062	0,288	1,000
Manager-Administration	34,33	16,80	2,044	0,041	0,410
Senior Manager-Administration	12,41	21,44	0,579	0,563	1,000

Source: Author's illustration of results generated by SPSS