The impact of digital technologies on employees' mental health and wellbeing in financial services in South Africa

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A research report submitted to the Faculty of Commerce, Law and Management, University of the Witwatersrand, in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business

Johannesburg, 2024

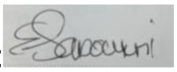
ABSTRACT

This study aimed to examine the influence of digital technologies on the mental health and wellbeing of employees within South African financial services organisations. The research framework was rooted in the Unified Theory of Acceptance and Use of Technology (UTAUT). The aim was to identify the influencing factors of adoption and the usage associated with digital technologies and analyse the implications of the digital technologies for employees' mental health and wellbeing in the context of the financial services sector in South Africa. A quantitative methodology was employed, sampling employees from financial services organisations in South Africa. A convenience sampling approach was utilised, resulting in a final sample size of 174 respondents. The data collection process involved the administration of an online survey questionnaire. To analyse the gathered data and test formulated hypotheses, Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM) were employed. Results of the study were consistent with the predictions of the UTAUT framework, indicating that performance expectancy, facilitating conditions, hedonic motivation, and social influence were the significant drivers of acceptance of digital technologies among users in financial services organisations. Furthermore, the study revealed significant positive correlations between the acceptance of digital technologies and both employee mental health and wellbeing. This signifies the interconnected nature of technology acceptance and its impact on employee outcomes. This study contributes to the existing knowledge by shedding light on the relationship between digital technologies, employee mental health, and wellbeing within the financial services sector in South Africa. The findings emphasise the importance of considering the multifaceted effects of technology on employees, urging organisations to recognise and address the implications for mental health and overall wellbeing in the workplace.

Keywords: Digital technologies, technology adoption, employee mental health, employee wellbeing, UTAUT

DECLARATION

I, Eleanor Sansovini, declare that this research report is my own work except as indicated in the references and acknowledgements. It is submitted in partial fulfilment of the requirements for the degree of Master of Management in the field of Digital Business at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination in this or any other university.

Name: Eleanor Sansovini Signature: 

Signed at Roodepoort

On the 29th day of February 2024

DEDICATION

This work is lovingly dedicated to my daughter, Madison, and my son, Marcelo. Daily, you are my inspiration, embodying the very essence of hope and the boundless energy that propels me forward. In your eyes, I see the future; in your laughter, I find the strength to chase my dreams. Your innate curiosity and zest for life remind me of the beauty in pursuit and the importance of following one's dreams and aspirations. It is in striving to be worthy of your admiration and to set an example for you to follow that I find my greatest motivation. This journey, with all its triumphs and challenges, is a testament to the inspiration you provide me every day. May this dedication serve as a small token of my immense love for you both and as a reminder that the pursuit of dreams is not just a solitary endeavour, but a journey enriched by those who inspire me most.

ACKNOWLEDGEMENTS

In completing the journey of my master's research, I extend my sincere gratitude to those whose guidance and support were invaluable. Each contribution has been a cornerstone in my academic endeavour, and for this, I am profoundly thankful.

Dr. Ayanda Magida deserves my first mention for her invaluable guidance and assistance throughout this research journey. The expertise and insights provided, have been inspiring.

I am grateful to Last Mamvura, who expertly guided me through the intricacies of analysis. His knowledge and patience were instrumental in navigating me through the complexities of data analytics.

The MMDB support group, established by the learners to assist everyone through their research, provided not just technical support but also laughter, encouragement, and the necessary nudges to keep us all moving forward. My heartfelt thanks go to this wonderful community.

To my parents, whose countless hours of babysitting allowed me the time and peace of mind to focus on my research, I owe a debt of gratitude. Your support has been a foundational element of my success.

My organisation has not only sponsored my research but also believed in my potential to bring valuable insights back into our operations. This faith in my abilities has been both an honour and a responsibility I have and will continue eagerly to fulfil.

I also wish to acknowledge my teams within my organisation, whose hard work behind the scenes kept our projects moving forward, allowing me the bandwidth to concentrate on my research during critical phases.

My friends have been a constant source of belief and motivation, pushing me to surpass my own expectations. Your confidence in me has been a source of strength.

Lastly, my children, who are my bedrock, have shown incredible understanding and support, intuitively knowing when I needed it most. Your love and patience have been the quiet force behind my endeavours.

This research is not just a reflection of my effort but a testament to the collective support and belief of each one of you. I am deeply grateful.

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CHAPTER 1. INTRODUCTION

1.1 Statement of purpose

The study examines the factors that influence the acceptance of digital technologies and analyses the impact on employees' mental health and wellbeing within the context of the financial services sector in South Africa.

1.2 Background of the study

The impact of digital transformation on employee wellbeing and mental health cannot be overstated, given its significant financial and human costs. Johnson et al. (2020) emphasises the critical nature of addressing employee mental health due to digital changes, highlighting the substantial implications for individuals and organisations. As Acemoglu and Autor (2011) articulate, digital transformations bring about a multitude of challenges, including shifts in workplace dynamics, a lack of preparation and support for employees, displacement, changes in communication and socialisation patterns, technostress, difficulties in maintaining work-life balance, and increased workloads. Introducing robotics and advanced information systems has revolutionised workplace practices (Wilson, 1997; Richter et al., 2018), marking a significant departure from traditional working environments.

Research focusing on the broader impacts of digital technologies, including studies by various scholars provides valuable insights into the economic growth and empowerment potential of digitalisation, particularly in developing economies like South Africa (Myovella et al.,2020; Warner & Wäger, 2019; Fernandez-Vidal et al., 2022). These studies highlight the critical role of strategic information and communication technology (ICT) infrastructure investment in maximising the benefits of digitalisation while addressing socioeconomic challenges such as unemployment and skills development.

Dennis (2021) highlights that the increasing prevalence of mental health issues among workers has escalated into a public health concern, making the workplace a crucial arena for mental health interventions (Petrie et al., 2018). Despite the growing emphasis on fostering mentally healthier work environments, evidence-based guidelines still need to be developed. Petrie et al. (2018) argues that creating supportive work environments highlight the importance of minimising harm, building resilience, promoting early help-seeking, and supporting recovery.

The evolution of the workforce and advancements in digital technology have led to adopting flexible working practices (FWPs), characterised by fluid boundaries around workspaces, schedules, and contracts. While FWPs have been amplified by the digital age and the COVID-19 pandemic, they also bring challenges such as social isolation and work-life balance tensions (Cooper & Baird, 2015; Groen et al., 2018;Como et al., 2021).

The pandemic-induced shift to remote work has highlighted the necessity for employers to reassess their support and engagement strategies, recognising the new work patterns and dependencies on digital technologies that may affect work-life balance and employee wellbeing (Ramsden-Knowles & Stainback; 2023; Donati et al., 2021; Carnevale & Hatak, 2020; Zhang et al., 2021; Kozinets, 2021; Singh et al., 2022).

Research suggests that FWPs can have both positive and negative effects on mental health. The benefits include reduced work-family conflict and enhanced autonomy. However, challenges like social isolation must also be considered, especially considering the pandemic's amplification of digital reliance and flexible work practices (Harvey et al., 2017).

Organisations could implement strategies that cultivate a supportive workplace culture to mitigate the adverse effects of digital transformation on employees. The fourth industrial revolution has spotlighted the necessity of considering the impacts of digital technologies on employee mental health beyond mere productivity and organisational outcomes. Gurbaxani and Dunkle (2019) and Perlow (2012) recommend that executives employ frameworks to guide digital transformation efforts, focusing on strategic, technological, human capital, and cultural considerations to mitigate risks and enhance employee wellbeing.

Ajigini (2023) highlights that digital transformation in the financial services sector in South Africa presents opportunities and challenges, as it compels organisations to harness the benefits of digital innovation while managing its complexities.

1.3 Research problem

Digital transformation (DT) in the workplace presents numerous challenges, including changes in job roles, the displacement of employees, increased workload, and the blurring of work-life boundaries (Acemoglu & Autor, 2011; Harvey et al., 2017). Employees can be harmed by these challenges, leading to increased stress, anxiety, and burnout. Digital transformations often involve redesigning job roles and tasks, increasing employee expectations and leading to anxiety about job security (Brougham & Haar, 2017; Groth et al., 2019). McClure (2017) highlighted the importance of reducing screen time to improve wellbeing, linking more screen time to increased levels of depression, anxiety, and burnout among employees.

Employees' wellbeing and mental health are crucial for their productivity and overall organisational success. Petrie et al. (2018) suggest a guideline for creating a healthy workplace, which involves modifying various aspects such as work design, management practices, personal resilience, and support systems. This framework suggests enhancement while addressing gaps where intervention studies are required. Organisations can create a mentally healthy workplace by understanding the evidence supporting this approach and actively implementing the strategies outlined in the framework (Petrie et al., 2018).

The digital workplace has blurred the boundaries between work and personal life, leading to increased workloads and challenges in achieving work-life balance (Acemoglu & Autor, 2010; Barley et al., 2010). Flexible working practices, such as remote work and flexible hours, have become more prevalent.

This study aims to explore the acceptance and perceived impact of digital technologies on employee wellbeing and mental health within financial services in the South African context.

1.4 Research questions

- What factors influence the acceptance of digital technologies in financial services in South Africa?
- What is the perceived influence of digital technologies on employee mental health in financial services in South Africa?
- What is the perceived influence of digital technologies on employee wellbeing in financial services in South Africa?

1.5 Rationale

The interest in the impact of digital technologies on wellbeing in the financial services sector in South Africa stems from observing the rapid digital transformation within the industry and its multifaceted effects on employees' and consumers' wellbeing. Integrating digital technologies in financial services has revolutionised how services are delivered and consumed, influencing work practices, consumer behaviour, and regulatory frameworks (Gomber et al. 2018).

Empirically, the study is grounded in observing a gap in existing literature, particularly in the context of emerging economies like South Africa. While there is substantial research on digital transformation in financial services globally, less attention has been paid to its impact on wellbeing, encompassing both positive aspects (e.g., enhanced access to services, improved work efficiency) and potential adverse outcomes (e.g., job displacement, digital divide). This study seeks to add to existing literature by investigating how digital technologies reshape employee wellbeing and mental health in the financial services sector. The study could contribute to the body of knowledge in an under-researched area, paving the way for future research endeavours, enriching the academic discourse on the implications of digital transformation.

This research is anticipated to contribute to the practice of management and digital business in several ways. By identifying the impact of digital technologies on wellbeing, the study provides insights that could guide the development of more humane digital transformation strategies, ensuring that technological advances contribute positively to the wellbeing of all stakeholders.

The research on the impact of digital technologies on wellbeing in the financial services sector in South Africa is not only of academic interest but also holds significant implications for the practice of digital business management. It addresses a critical gap in understanding the human side of digital transformations, offering valuable insights for creating more inclusive, sustainable, and wellbeing-oriented digital financial ecosystems.

1.6 Delimitations of the study

The study is confined to employees within financial services organisations in South Africa who have been exposed to digital technologies. This population limitation suggests that the findings may not be universally applicable across different regions or industries, highlighting a cautious approach to generalising the results. The selected sample may not fully represent the diversity within the broader target population, potentially overlooking variations in socioeconomic status, education level, and cultural backgrounds.

External factors, such as organisational changes and technological advancements, which could influence the participants' perceptions and experiences of digital transformation, are recognised as beyond the researchers' control. These elements could impact the study's outcomes, indicating a limitation in accounting for external influences.

1.7 Definition of terms

Digital transformation encompasses adopting new strategies and business models facilitated by the emergence of information technologies. As articulated by Furr et al. (2022), this concept involves incorporating advanced technologies into various aspects of business operations, leading to changes in representation, connectivity, and aggregation (Adner et al., 2019). The definition of digital transformation varies significantly across industries and even among organisations within the same industry due to differing objectives, access to critical technologies, and technology architectures, highlighting the complexity and contingent nature of digital transformation (Furr et al., 2022).

The digital revolution, marked by technological disruption and primarily driven by digitisation, is identified by Armstrong and Lee (2021) as a significant long-term driver of change globally, affecting organisational structures, processes, strategies, and jobs. This disruption necessitates organisations to adapt, viewing these changes as opportunities or challenges with varying impacts across industries, functions, and occupations.

Technology acceptance is the willingness and intention of individuals to adopt and use a particular technology (Venkatesh et al., 2012).

Employee mental health refers to the psychological state and emotional well-being of individuals in the workplace (Zhou et al., 2022; Sun et al., 2022).

Employee Wellbeing encompasses the holistic state of comfort, health, and happiness experienced by individuals within the work environment (Page & Vella-Brodrick, 2009).

1.8 Assumptions

- As an organisation digitally transforms, it has an impact on the wellbeing and mental health of the employees.
- Due to the stigma attached to mental wellbeing, participants would not be forthcoming to the extent of the problem within financial services organisations.
- This study assumed respondents would share their experiences truthfully rather than concealing their fears and conforming to their organisational positions.

1.9 Report Outline

1.9.1 *Chapter 1: Introduction*

Chapter 1 lays the foundation for the study, starting with the purpose (Section 1.1) to explore the factors affecting the adoption and use of digital technologies and their impact on the mental health and wellbeing of employees within South

Africa's financial services sector. The background (Section 1.2) emphasises the significant effects of digital transformation on mental health and wellbeing, advocating for ICT and supportive workplace practices to effectively manage its challenges and benefits. The research problem is outlined in (Section 1.3), with the research questions presented in (Section 1.4). The rationale (Section 1.5) discusses the study's focus on both the positive and negative consequences of digital transformation, while the delimitations (Section 1.6) caution against overgeneralising the findings concerning employee wellbeing. Definitions of key terms and the study's assumptions (Section 1.8) highlight how digital transformation impacts employee wellbeing and mental health, acknowledging the potential for stigma to limit participant openness in financial services. Finally, (Section 1.9) offers an outline of the report structure for Chapter 1.

1.9.2 *Chapter 2: Literature Review and Theoretical Framework*

Chapter 2 begins with an introduction (section 2.1) and a background discussion (section 2.2), which delves into the scholarly concerns regarding the impact of the fourth industrial revolution's rapid technological advancements on workplace dynamics. This is followed by the analytical framework (section 2.3), where the theoretical lenses and methodologies applied to scrutinise the effects of digital transformation on employee mental health and wellbeing are outlined. The chapter concludes (section 2.4) by compiling the literature review's key findings, emphasising their relevance to the research questions and objectives.

1.9.3 *Chapter 3: Research Methodology*

Chapter 3 begins with a detailed examination of the postpositivist worldview in (section 3.1). It proceeds to describe the applied research methodology utilised in (section 3.2), followed by the elaboration on a survey design approach and the implementation of the Qualtrics tool for gathering data in (section 3.3) and (section 3.4), respectively. Discussion on the targeted population and sample size takes place in (section 3.5), which leads into an overview of the research instrument in (section 3.6). The procedure for collecting data is outlined in (section 3.7), with data analysis techniques and interpretation methods detailed in (section 3.8). The chapter concludes by addressing quality assurance practices in (section 3.9) and ethical considerations in (section 3.10), ensuring the study's integrity and adherence to ethical standards.

1.9.4 *Chapter 4: Presentation of Results*

Chapter 4 presents a comprehensive statistical analysis of the collected data supporting the study's hypotheses and offers insights into the factors influencing the acceptance of digital technologies in South Africa's financial services sector and their effects on employee wellbeing and mental health. As part of the presentation the results from the tests employed in the study are presented: reliability analysis, exploratory factor analysis (EFA), descriptive analysis, correlation analysis, confirmatory factor analysis (CFA), and structural equation modelling (SEM).

- **Reliability Analysis:** The reliability of the measurement scale was evaluated using Cronbach’s alpha to measure internal consistency.
- **Exploratory Factor Analysis (EFA):** The analysis revealed the underlying factor structure of the constructs being measured. Its main aim was to detect patterns and relationships among the observed variables, facilitating a deeper insight into the acceptance of digital technologies and its related factors in the financial services sector.
- **Descriptive Analysis:** This involved analysing responses' central tendency and variability on a 7-point Likert scale. The analysis revealed high mean scores across various constructs, indicating a consensus favouring technology adoption.
- **Correlation Analysis:** This analysis assessed the strength of relationships among variables, revealing significant positive correlations between the dependent variable (technology adoption) and explanatory variables like performance expectancy and facilitating conditions.
- **Confirmatory Factor Analysis (CFA):** This was conducted to validate the EFA results. The model showed a good fit, with various indices indicating its appropriateness.

- **Structural Equation Modelling (SEM):** SEM was used to explore the underlying structural relationships among validated constructs, revealing significant predictors of digital technology acceptance and its impact on employee mental health and wellbeing.

1.9.5 *Chapter 5: Discussion of the Results*

Chapter 5 presents an exploration of the impacts of digital technologies on the mental health and wellbeing of employees within a financial services organisation in South Africa. It was found that significant relationships existed between performance expectancy, facilitating conditions, and hedonic motivation with the acceptance of digital technologies. The acceptance of these technologies was further noted to have a positive correlation with employee mental health and wellbeing. The discussion extended across several hypotheses, each examined for its influence on technology acceptance and subsequent effects on employee wellbeing.

1.9.6 *Chapter 6: Conclusion and Recommendations*

Chapter 6 synthesises the findings on the impact of digital technologies on the mental health and wellbeing of employees in South Africa's financial services sector. It aims to address the research questions in Chapter 1, integrating insights from the literature review, data analysis, and study results into comprehensive conclusions and actionable recommendations for enhancing the acceptance of digital technologies in the workplace.

CHAPTER 2. LITERATURE REVIEW AND THEORETICAL FRAMEWORK

2.1 Introduction

This study focuses on investigating the impact of digital technologies on employee mental health and employee wellbeing in the context of South African financial services organisations. Literature is reviewed in this study, with the aim of formulating hypotheses and developing the conceptual framework of the study. This chapter covers the introduction (section 2.1), background discussion (section 2.2.), analytical framework (section 2.3), and the conclusion of the literature review (section 2.4).

2.2 Background Discussion

Researchers have raised concerns about the potential impacts of the rapid and extensive technological advancements brought about by the fourth industrial revolution (4IR) on workplaces, including the potential displacement of employees (Trennery et al., 2021). Furthermore, it has been observed that the swift progress of digital technologies is driving the revolutionisation of work and organisations in Africa. However, the design of technology in the workplace, often aimed at boosting productivity and enhancing organisational outcomes, necessitates more careful consideration of its effects on employees (Trennery et al., 2021).

The prominence of digital transformation in global strategies has been made evident by the dominance of startups such as Google, Booking.com, Alibaba, and Amazon, which have redefined traditional industries and shattered global boundaries, fostering the belief in the potential of digital transformation to revolutionise every aspect (Furr et al., 2022).

The focus on transformation and change beyond mere technology in 4IR is argued by Armstrong and Lee (2021), where the effective and successful use of technology to transform and enhance long-term processes, products, or systems emerges as a significant challenge. Dittes et al. (2019) observed the extension of digital work beyond the provision of new technology, emphasising the importance of people's adaptability and processes. Further, Davenport and Westerman (2018) stress the influence of factors beyond technology on successful digital transformations, necessitating changes in business conduct, investments in skills and infrastructure, and the integration of people, machines, and processes. Gurbaxani and Dunkle (2019) acknowledge that the complexity of embarking on a digital transformation, requires a clear understanding of the intent and consideration of various factors. Digital transformations are predominantly tech-driven, and many organisations struggle with responding to these challenges, often treating new technology concepts as trends rather than business imperatives (Gurbaxani & Dunkle, 2019, p. 3).

The predominantly negative impact of technology on mental health in the workplace is attributed to heightened demands and changes in employees' future perspectives, leading to costs for both employers and employees (Harvey et al., 2017). Whiteford et al. (2013) reinforces the significant economic and health system impacts of digital technologies. According to Trennery et al. (2021), it is important for organisations to understand how to mitigate the negative impacts of digital technologies and promote positive technology relationships.

The literature review aims to understand the challenges of digital technologies for employees in the South African financial services sector, which factors influence the acceptance of digital technologies, and the influence of digital technologies on employees' mental health and wellbeing.

2.3 Analytical framework

2.3.1 *The unified theory of acceptance and use of technology (UTAUT)*

Venkatesh et al. (2003) developed the Unified Theory of Acceptance and Use of Technology (UTAUT) to elucidate how users' intentions to use an Information System (IS) and subsequent usage behaviour are influenced. According to the theory, four essential constructs (performance expectancy, effort expectancy, social influence, and facilitating conditions) directly determine the user's intention and behaviour towards usage. Additionally, gender, age, experience, and voluntariness of use are proposed to moderate the impact of these four critical constructs on usage intention and behaviour (Venkatesh et al., 2003). This study utilised the four factors (performance expectancy, effort expectancy, social influence, and facilitating conditions). The study extended the model to include habit and hedonic motivation as predictors of technology acceptance. In addition, the model was extended to include the impact of accepting the technology on employees' wellbeing and mental health. The following sections focus on developing the hypotheses, building from the UTAUT guided by prior studies.

2.3.2 *What factors influence the acceptance of digital technologies in financial services in South Africa?*

The UTAUT suggests that four key factors (performance expectancy, effort expectancy, social influence, and facilitating conditions) and four moderators (age, gender, experience, and voluntariness) predict technology adoption (Venkatesh et al., 2003). The need for technology to be adopted and assimilated into the organisation to combat technology anxiety, and the influencing factors identified below attempt to provide more context on the acceptance of these digital technologies.

Performance Expectancy (PE)

Performance expectancy is defined by Venkatesh et al. (2003) that the belief when using technologies that it will increase the individuals job performance. This belief is coupled to the perceived usefulness of technology (Zhou et al., 2022). Performance expectancy is a primary factor influencing an individual's intention to adopt technology (Venkatesh et al., 2003; Yohanes et al., 2020).

Chatterjee et al. (2021) determines further that attitude is influenced by PE and is crucial for an individual's inclination towards adopting AI technologies. Shaikh et al. (2021) emphasise PE as a vital precursor in technology acceptance, asserting a positive impact on adoption intention and attitude towards technologies, moderated by perceived risk and effort expectancy. This suggests that adoption intention increases when technology is perceived as both easy to use and valuable, even amid perceived risks, highlighting the significance of PE in shaping behavioural intentions towards technology adoption.

Kurniasari et al. (2020) and Xie et al. (2021) reinforce the role of PE as a critical determinant in the adoption of FinTech, suggesting that belief in the technology's ability to enhance business performance positively affects adoption intentions. They highlight the direct correlation between PE and behavioural intention, underscoring the importance of perceived effectiveness and efficiency gains from technology in organisational contexts.

Rahim et al. (2022) confirm that PE significantly influences the behavioural intention towards adopting FinTech, indicating a higher likelihood of technology acceptance when perceived as enhancing performance. However, Hassan et al. (2023) presents a contrasting view, suggesting that PE did not significantly impact the behavioural intention to use FinTech services in insurance-related activities. This suggests that factors such as effort expectancy, quality (information, system, and service), and perceived risk play more critical roles in accepting and integrating digital technologies within financial organisations, particularly in the insurance industry.

Based on the discussion, the following hypothesis was made:

Hypothesis 1 (H1): Favourable perceptions of performance expectancy positively influence acceptance of digital technologies.

Effort Expectancy (EE)

Venkatesh et al. (2003) noted that effort expectancy (EE) was a key factor in the acceptance of technology. EE is referred to as the perceived ease of using a system and closely corresponds to the "ease of use" construct in the Diffusion of Innovation (DoI) theory. Venkatesh et al. (2003) further emphasises the importance of designing user-friendly technologies and the role of perceived effortlessness in enhancing adoption rates. This is evident across diverse applications, including online learning environments (Batucan et al., 2022), electronic banking systems (Fedorko et al., 2021), AI-based Customer Relationship Management in B2B contexts (Chatterjee et al., 2021), and the usage of social networking sites by the elderly post-pandemic in Chile (Ramírez-Correa et al., 2023). The studies collectively emphasise the critical role of effort expectancy (EE) in influencing the acceptance and use of various digital technologies

Based on the above, the following was hypothesised:

Hypothesis 2 (H2): Favourable perception of effort expectancy positively influences acceptance of digital technologies.

Facilitating Conditions (FC)

Facilitating conditions (FC) refer to the perception by an individual of the extent to which the necessary technological infrastructure is believed to be in place, supporting the utilisation of new technologies. The simplification of the use of technologies such as Artificial Intelligence (AI) is seen when the current technological infrastructure is user-friendly and supports the utilisation of the system by employees (Venkatesh et al., 2012). Chatterjee (2021) found that a significant role in the acceptance of a particular technology is played by facilitating conditions, which exert a considerable influence on the adoption and usage behaviour of innovative technologies.

Taherdoost (2018) emphasises the need for appropriate support and resources, such as help desks, technical support, and adequate infrastructure, for the effective utilisation of technology by employees. This is further supported by Shaikh et al. (2021) and Singh et al. (2020) who highlighted that facilitating conditions can include adequate training programs, accessible technical support, and well-designed infrastructure with a culture that encourages and supports technological innovation.

Furthermore, Batucan et al. (2022) stressed the significance of facilitating conditions in influencing technology acceptance and their direct impact on both behavioural intention and user behaviour. Specifically, Batucan et al. (2022) found that facilitating conditions have a positive effect on students' behavioural intention towards using online learning systems, as well as on their actual use behaviour. Sukendro et al. (2020) also found that facilitating conditions play a key role in influencing adoption and use of technologies.

The literature emphasises that for technology to be effectively integrated and utilised, the availability of adequate support, infrastructure, and a supportive culture are essential (Venkatesh et al., 2003, Taherdoost (2018), Batucan et al., 2022, Sukendro et al., 2020).

Based on the discussion, the following hypothesis was made:

Hypothesis 3 (H3): Facilitating conditions positively influences acceptance of digital technologies.

Hedonic Motivation (HM)

Hedonic motivation refers to the pleasure or enjoyment derived from using a system which is a critical factor in determining both acceptance and the usage of technology (Chao, 2019; Venkatesh et al., 2012). The literature has regularly shown that HM and the likelihood of individuals accepting and using technology displays an encouraging correlation (Venkatesh et al., 2012; Nikolopoulou et al., 2020; Gharrah and Aljaafreh, 2021). The impact of technology on employees, who experience both the positive and negative narratives surrounding its adoption, further emphasises the complexity of technological acceptance. Anxiety, technophobia, and scepticism often arise when adapting to new digital technologies which becomes overwhelming (Venkatesh et al., 2012).

The Motivational Model (MM) distinguishes between intrinsic and extrinsic motivations, highlighting how perceived enjoyment, a form of hedonic motivation, significantly influences technology acceptance (Taherdoost, 2018). This is supported by studies demonstrating that both perceived usefulness (extrinsic motivation) and perceived enjoyment (intrinsic motivation) impact behavioural intentions and actual system use, suggesting a positive effect of hedonic motivation on digital technology acceptance (Hartline et al., 2021).

Research focusing on specific technology applications, such as mobile internet usage by teachers, confirms the importance of HM in predicting behavioural intentions to use technology in teaching (Nikolopoulou et al., 2021). These findings highlight the critical role of user experience and satisfaction in technology acceptance models, emphasising the need for enjoyable and engaging technology designs.

Furthermore, the impact of HM on technology acceptance and use is explored in different contexts, indicating that its influence varies depending on whether technology use is driven by intrinsic motivations related to enjoyment or fun rather than purely practical purposes (Tamilmani et al., 2019). The study by Schomakers et al. (2022) extends this analysis to the acceptance of lifestyle versus therapy mobile health apps, finding that hedonic motivation significantly predicts behavioural intentions towards both types of apps, underlining the importance of enjoyment, fun, habit, social influence, and trust in the adoption of mobile health applications.

In summary, the literature strongly supports the inclusion of hedonic motivation as a critical factor in understanding and predicting the acceptance and use of digital technologies, emphasising its role in enhancing user experience and satisfaction to drive technology adoption and usage.

Based on the discussion, the following hypothesis was made:

Hypothesis 4 (H4): Hedonic motivation positively influences acceptance of digital technologies.

Social Influence (SI)

The impact of Social Influence (SI) on technology acceptance and usage behaviours has been extensively studied, with the social environment playing a major role in shaping individuals' behaviours towards technology use. Previous research, such as that by Alshammari (2021), has demonstrated a significant effect of SI on the acceptance of business intelligence (BI) systems. Venkatesh et al. (2012) suggests that technology acceptance is positively influenced by social influence, particularly in mandatory settings, where its effect is noted to be stronger during the initial stages of technology adoption but decreases as users gain more experience with the technology. This underscores the importance of social factors, including the opinions of significant others and the perceived prestige associated with technology use, in understanding technology acceptance behaviours.

Kulviwat et al. (2009) further confirm that SI positively affects technology acceptance, especially for high-tech innovations. However, Alshammari (2021) found that SI did not significantly impact the teaching staff's behavioural intention towards using virtual classrooms, suggesting that SI's influence might vary across different contexts. Batucan et al. (2022) substantiates that SI significantly impacts behavioural intention towards technology acceptance, highlighting the role of perceptions of leadership in shaping an individual's intention to use technology.

Matema and Kariuki (2022) examined the relationship between social media and social cohesion, noting that while social media can promote social cohesion by serving as spaces for engagement and community building. However social media also presents challenges, such as misinformation and the potential to reinforce intra-group cohesion at the expense of broader social cohesion. This indicates that the impact of social media on social cohesion is contingent on its use and regulation.

Based on the discussion, the following hypothesis was made:

Hypothesis 5 (H5): Social Influence has a positive influence on technology acceptance.

Habit (HA)

The concept of habit (HA) refers to the extent to which individuals engage in behaviours automatically (Casey & Wilson-Evered, 2012). Described as the unconscious use of a system, habit involves actions that become customary or almost reflexive (Moorthy et al., 2019). The impact of habit on the behavioural intentions of users to adopt a system has been confirmed by several studies, including those by Huang and Kao (2015) and Gharrah and Aljaafreh (2021).

Limayem et al. (2007) emphasised the need for employees to develop new habits to effectively execute their roles in the digital workplace, prompted by the technological redesign of job roles and tasks. Venkatesh et al. (2012) further, demonstrated the positive impact of habitual technology use on users' behavioural intentions and actual technology use. Habitual behaviours, which develop through frequent and consistent use over time, become automatic and influence technology use decisions rather than deliberate decision-making processes.

Nikolopoulou et al. (2021) also found a significant influence of habit on the acceptance of digital technologies, especially regarding mobile internet use by teachers. The study found that habit, hedonic motivation, performance expectancy, and technological instructive knowledge significantly predict teachers' intentions to use mobile internet. This confirms habit's vital role in shaping teachers' willingness to incorporate mobile internet into their teaching practices, which supports the hypothesis that habit positively influences technology acceptance, underscoring the critical role of habitual behaviours in technology adoption models.

Based on the discussion, the following hypothesis was made:

Hypothesis 6 (H6): Habit has a positive influence on acceptance of digital technologies.

2.3.3 *The perceived influence of digital technologies (DT) on employee mental health (MH) and Wellbeing (WB) in financial services in South Africa*

Employee Mental Health (MH)

Defined by the World Health Organisation (2020) as essential throughout all life stages, mental health influences stress management, interactions with others, and decision-making processes. The term employee mental health pertains to the psychological state and overall wellbeing of individuals within the professional setting (Zhou et al., 2022). Employee mental health encompasses elements such as stress, anxiety, depression, and the general emotional health that can exert an influence on an employee's capacity to perform optimally in the workplace (Sun et al., 2022). Research into employee mental health often centre on investigating the implications of diverse workplace determinants, including but not limited to social media utilisation, occupational demands, and organisational support, on the mental wellbeing of employees (Zhou et al., 2022; Cai, 2022).

There is an increasing expectation for employers to protect the mental wellbeing of employees, evidenced by a sixty-four percent rise in reported mental health issues within the financial sector (Lock Associates Group, 2024; Corrigan, 2022; Ramsden-Knowles & Stainback, 2023). Research indicates that the UK workforce, particularly within the finance sector, sees approximately three hundred thousand employees leaving their jobs each year due to mental health issues. Additionally, it has been revealed that 74% of workers feel that their companies are taking insufficient steps to safeguard mental health, and forty-two percent would utilise emotional wellbeing support if provided (Lock Associates Group, 2024). According to Corrigan (2022), the decision by 50% of employees to leave their jobs in 2021 was attributed to mental health reasons. McGregor (2023) indicates it is expected that more than half of the population in middle and high-income countries will experience at least one mental health issue during their lifetime, with a decline in mental health reported by 42% of global employees since the onset of the COVID-19 pandemic. A significant impact on workplace productivity is seen due to the rising symptoms of burnout among employees and leaders. An estimation by the World Health Organization suggests that conditions such as depression and anxiety are costing the global economy about $1 trillion annually in lost productivity (Brassey et al., 2021).

The exploration of the role digitalisation plays in supporting mental health was conducted by Sun et al. (2022), where it was found that a positive influence on employee mental health is exerted by the acceptance of digital technologies, with wellbeing at work acting as a mediator. A significant positive relationship between digitalisation and employee mental health is identified, suggesting that enhanced IT capabilities contribute to better workplace wellbeing. The impact of digitalisation on mental health, through aspects such as IT infrastructure, business spanning, and a proactive stance, is the focus of this study. This relationship suggests that mental health can be supported by the effective use of digital technologies, which fosters a work environment that is more engaging, supportive, and efficient, ultimately leading to the improved wellbeing of employees (Selimović et al. 2021).

Christensen et al. (2020) provided a balanced perspective on the impact of digitalisation acknowledging the potential benefits and drawbacks on the psychosocial work environment and employee wellbeing. This understanding is deemed crucial for the effective implementation of digital solutions. The exploration of digitalisation's consequences on the psychosocial work environment, employee health, and wellbeing by Christensen et al., (2020), involved an examination of various studies to discern the influence of workplace technology on psychological and somatic symptoms, wellbeing, and job-related factors. While the review identifies both positive and negative effects of technology on work and health outcomes, a definitive conclusion on the universal positive impact of digital technology acceptance on mental health outcomes is not provided. Instead, it is suggested that the impact of digital technologies on employee mental health is nuanced and contingent upon several factors, including the manner of technology implementation and integration into work processes. Positive outcomes include enhanced communication, flexibility, and increased work satisfaction (Christensen et al. 2020).

In contrast, adverse outcomes encompass increased work intensity, blurred work-personal life boundaries, and the risk of information overload, all contributing to stress and other mental health issues. It suggests a complex relationship between digitalisation and employee wellbeing, dependent on the practices of implementation and integration (Christensen et al. 2020) who further suggests that the impact of digital technologies on employee mental health is dependent on factors like the technology's nature, the organisational context of its deployment, the extent of work practice changes it introduces, the support provided to employees during transitions, and individual employee differences. These factors are suggested to affect how technology impacts work-life balance, job satisfaction, stress levels, and overall wellbeing (Christensen et al., 2020).

Further enriched by Atluri et al., 2016 and mental health professionals, vital digital offerings for workplace wellbeing strategies were identified. Brassey et al., (2021) highlighted the global mental health crisis, exacerbated by the COVID-19 pandemic, and the potential for digital solutions to provide accessible, stigma-reducing support.

The literature clarifies the importance of mental health in the workplace, revealing an increasing demand for employers to address mental health issues, particularly spotlighted within high-stress sectors like finance, where a notable rise in mental health concerns has been documented (Atluri et al. 2016).

The investigation into the impact of digital technologies on employee mental health, illustrates the positive correlation between digital technology adoption and enhanced mental wellbeing at work (Sun et al., 2022; Brassey et al., 2021). However, navigating mental health challenges in the workplace requires a balanced integration of digital solutions tailored to enhance employee wellbeing while mitigating potential negative repercussions of technological advancements.

Based on the discussion, the following hypothesis was made:

Hypothesis 7 (H7): Acceptance of digital technologies positively influences employee mental health.

Employee Wellbeing (WB)

Employee wellbeing denotes the comprehensive condition of experiencing comfort, good health, and contentment within the work environment (Page & Vella-Brodrick, 2009). The definition is further expanded to encompass physical, mental, and emotional aspects (Diener et al., 2010).

Shamsi et al. (2021) stressed the role of technology acceptance in enhancing the work-related wellbeing of employees during the COVID-19 pandemic, finding that technology acceptance had a positive and significant impact on work engagement. This finding is corroborated by Molino et al. (2020), who confirmed the positive effect of digital technology acceptance on work engagement, with resilience and opportunities for information and training serving as mediators. In addition, Sun et al. (2022) found that digitalisation has a positive relationship between digitalisation and employee wellbeing, mainly through its mediating effect on mental health, highlighting the importance of IT infrastructure in fostering a healthier work environment. Trenerry et al. (2021) also emphasised the critical role of technology acceptance in promoting better employee wellbeing through a positive work environment.

However, Khoza (2022) found no significant correlation between technology acceptance and employee wellbeing. Studies also acknowledge the challenges associated with technological advancements and digital transformation, including anxiety and mental health concerns related to fears of job displacement and the rapid pace of technological change (Johnson et al.,2020; Groth et al.,2019; Brougham & Haar, 2017). Kozanoglu and Abedin (2021) recommended the development of digital literacy as a means for successful adaptation to digital transformations), emphasising the importance of equipping employees with the necessary skills for effective technology utilisation.

Competing narratives regarding the hopes and fears of technology's impact are noted by McClure (2017). Galanti et al., 2023 highlight that technophobia and technostress as a psychological response to the challenges of adapting to new digital technologies can lead to biological stress reactions which directly affects individuals' mental health and wellbeing, manifesting as anxiety, fatigue, and scepticism. Factors contributing to technostress in the workplace include the blurring of work and family life, which negatively affect employees and their family member's mental health (Lebeau, 2022).

Stress resulting from the inability to cope with the demands of organisational computer usage is contextualised by Tarafdar and Ragu-Nathan (2005), who identify five dimensions.

- Techno-overload: Employees feel forced to work faster and longer because of technology.
- Techno-invasion: Technology invades personal life, causing loss of privacy and control over one's time.

- Techno-complexity: Users feel overwhelmed by the complexity of technology, resulting in feelings of incompetence.
- Techno-insecurity: Rapid changes in ICTs cause concerns about job security due to the need for continual skill upgrades.
- Techno-uncertainty: Ongoing advancements in ICTs create unease among users, as they must constantly adapt to new technologies.

These dimensions have been shown to contribute to stress among technology users, negatively impacting their productivity and supporting the hypothesis that technostress creators significantly negatively influence individual productivity.

Based on the discussion, the following hypothesis was made:

Hypothesis 8 (H8): Acceptance of digital technologies positively influences employee wellbeing.

2.4 Conceptual Framework

The conceptual framework for this study is based on the UTAUT which identifies performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and habit as predictors of technology acceptance. The UTAUT is further extended in this study to incorporate aspects of mental health and wellbeing in the workplace. Thus, the study hypothesises that acceptance of digital technologies in the workplace could improve the wellbeing and mental health of employees within the South African financial services industry. Figure 2.1 shows the conceptual framework, revealing the hypotheses formulated in this chapter.

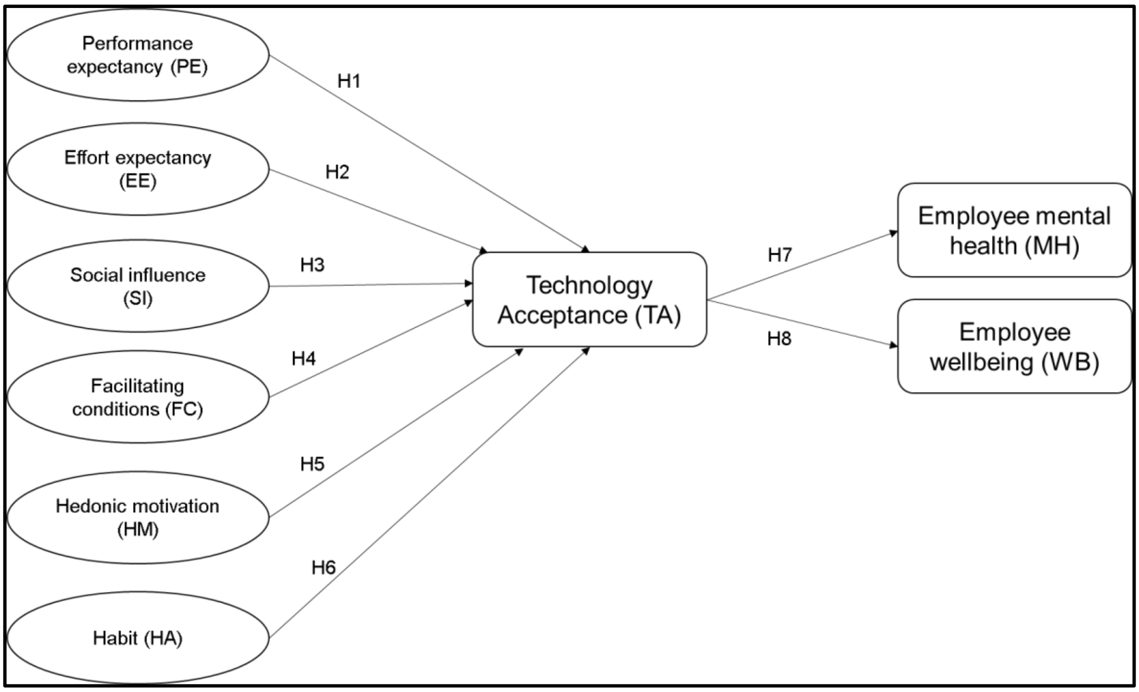

Figure 2-1 Conceptual framework

2.5 Conclusion of Literature Review

The literature review focused on the factors that influence the acceptance of digital technologies and the influence of digital technologies on employee mental health and wellbeing. The insights drawn from the Unified Theory of Acceptance and Use of Technology (UTAUT) and the examination of various factors influencing the acceptance of digital technologies emphasises the complexity of technology adoption and its consequential effects on employees in the digital age.

The evidence further highlights the positive potential of the acceptance of digital technology in enhancing work-related wellbeing and mental health, as demonstrated in the various studies. However, the literature also acknowledges the challenges and potential negative impacts of rapid digitalisation, including technostress and the blurring of work and family life, which could undermine employee wellbeing.

The theoretical exploration reveals that while digital technologies offer opportunities for improving work engagement and creating healthier work environments, the success of these technologies in promoting employee wellbeing is contingent upon several factors. These include designing and implementing technology, the organisational context, and providing adequate employee support and training.

Moreover, the discussion on the influencers of digital technology acceptance, including performance expectancy, effort expectancy, social influence, facilitating conditions, and hedonic motivation, illustrates the intricate relationship between technology use and employee mental health outcomes. While significant, the positive influence of the acceptance of digital technology on employee mental health and wellbeing is subtle and requires a balanced approach to maximise benefits and mitigate risks.

CHAPTER 3. RESEARCH METHODOLOGY

3.1 Introduction

Chapter 3 focuses on research methodology used to achieve the objectives of the study. Issues discussed in this chapter include the research paradigm, research design, the population and sampling methods, the research instrument, collection of data, analysis of data, quality assurance and ethical considerations,

3.2 Research Paradigm

The research adopted a Postpositivist Worldview, guided by a quantitative methodology that acknowledges the intricacies of human behaviour and actions (Saunders et al., 2009). In line with positivist principles, the study aimed to identify and examine the relationships between variables to analyse cause and effect, particularly focusing on how digital technology adoption affects employee mental health and wellbeing.

Positivism relies on empirical evidence obtained through observation and experimentation (Creswell & Creswell, 2018). The structured survey approach employed in this study allowed for the testing of hypotheses related to digital technology acceptance and its impact on wellbeing.

The research was grounded in positivist traditions, striving for an objective quantification of the impact of acceptance of digital technologies.

Furthermore, the study's reliance on empirical evidence underscores a commitment to positivist standards of objective measurement and hypothesis testing (Saunders et al., 2009). The focus on uncovering cause-and-effect relationships within the financial services sector further exemplifies the positivist aim to comprehend the world through measurable entities.

The study’s foundation in objectivity, empirical investigation, hypothesis examination, and the quest for generalisable knowledge situates it firmly within the positivist framework (Saunders et al., 2009). The positivist philosophy was particularly suited to the research questions posed, enhancing the study's rigor and validity.

3.3 Research approach

Social science researchers utilise various research techniques, procedures, and methods to gather information on a situation, issue, problem, or phenomenon (Kumar, 2014). Regarding the mode of inquiry, social research employs quantitative, qualitative, and mixed methods approaches to answer research questions (Kumar, 2014). This study employed a quantitative research approach, which was suitable for analysing and measuring variables using numerical data. This approach enables the aggregation and analysis of data, facilitating the identification of patterns, relationships, and trends (Kumar, 2014). The quantitative approach is consistent with the positivist philosophy which emphasises objectivity in the collection and analysis of data (Creswell & Creswell, 2018).

3.4 Research design

The research journey to find answers to research questions is guided by a research design which aims to achieve validity, objectivity, accuracy, and efficiency (Kumar, 2014). The research design outlines the methods and procedures employed during the research process.

For this study, a survey design was adopted as it enables the quantitative description of trends, attitudes, and opinions within a population and the examination of associations among variables within a sample of that population (Saunders et al., 2009). Surveys are helpful for examining associations among variables within a sample, playing a crucial role in identifying and analysing relationships and dependencies observed within the target population (Creswell & Creswell, 2018). The versatility of survey designs is highlighted by their adeptness at addressing descriptive questions, exploring relationships between variables, and investigating predictive relationships over time, making them a versatile tool for various research objectives. Additionally, the efficiency and objectivity of surveys are attributed to their structured nature, which aids in the simultaneous distribution to many participants, thereby being time and cost-effective, and the standardised format, which helps maintain consistency in responses (Kumar, 2014).

However, as Kumar (2014) suggests, the limitations of survey design in capturing depth and nuance are acknowledged compared to qualitative methods like interviews or focus groups. This significant drawback is noted when the need arises to explore complex behaviours, motivations, or attitudes more deeply. The susceptibility of survey responses to various biases, such as social desirability bias, where respondents may not express their true feelings or behaviours, is recognised as affecting the accuracy of data collected (Kumar, 2014). The issue of low response rates, especially in surveys administered online or via mail, leading to non-response bias, raises concerns about the representativeness of the data and, consequently, the validity of the research findings. Furthermore, the potential for misinterpretation of questions due to the absence of a researcher to provide clarifications is mentioned, leading to variability in responses that may not accurately reflect participants' opinions or experiences (Kumar, 2014)

Despite the limitations of survey, the survey design was appropriate in this study as it enables the collection of data from a wide sample. Surveys, especially administered online, are important because they can reach a wide and dispersed sample (Creswell & Creswell, 2018).

3.5 Data collection methods

Information was gathered through primary sources, utilising an online questionnaire as the data collection tool. The online questionnaire consisted of sections addressing a specific research question. Additionally, there was a section focusing on gathering demographic information from the participants.

The Qualtrics platform was used as a medium to distribute the questionnaire. This platform offers several advantages, as it allows participation from individuals in various geographic locations and offers a cost-effective means of administering the questionnaire (Kumar, 2014).

A cover letter accompanied the questionnaire, introducing the researcher, outlining the main objectives of the study, explaining the study's relevance, providing general instructions, emphasising the voluntary nature of participation, ensuring the anonymity of respondents' information, including a contact number for any inquiries, and expressing gratitude for the participants' involvement. The questions in the questionnaire were in the form of open and closed-ended questions, presented in a structured manner, allowing respondents to select the most relevant answer (Kumar, 2014). Please refer to Appendix A for a visual representation of the questionnaire.

3.6 Population and sample

3.6.1 *Population*

The study was limited to a specific population including employees who are employed in financial services organisations in South Africa and have been exposed to digital technologies. The population size in this study was unknown because of the diverse nature of the study. It was difficult to estimate the total number of employees working in financial services organisations across South Africa. The study therefore utilised non-probability sampling methods to select a representative sample.

3.6.2 *Sampling*

Sampling involves selecting a smaller subset, known as a sample, from a larger group, referred to as the sampling population, to estimate or predict unknown information, situations, or outcomes within the larger group (Kumar, 2014). The sample represents a subgroup representative of the entire population under investigation.

3.6.3 *Sampling method*

Non-random/non-probability sampling methods were employed for this study. Specifically, the accidental type of non-random sampling was used, which involves selecting a location where potential respondents are likely to be found, irrespective of convenience. Additionally, snowball sampling was utilised, wherein initial individuals within a group or organisation were selected, and the required information was collected from them. These individuals were then asked to identify other members within the group or organisation who would become part of the sample. Data was collected from them, and they were requested to identify further members.

Respondents employed by financial services organisations in South Africa were included in the sample. In addition, to reach financial services employees, the survey link was shared on LinkedIn. Using a convenience sampling method, participants were administered an online survey, from which 210 responses were received. The data collected were then subjected to a cleaning process to address missing values and incomplete responses. During this process, 36 responses were identified as incomplete, with these participants having discontinued the survey after only completing the first section, which pertained to demographic information. As a result, these incomplete responses were removed from the dataset, leaving 174 valid responses available for analysis. Consequently, a final sample size of 174 participants was utilised for the study.

3.7 The research instrument

The study used critical constructs derived from the Unified Theory of Acceptance and Use of Technology (UTAUT) framework and relevant concepts from the literature.

The hypotheses developed in the study were derived from the theoretical framework. They described the expected relationships between the constructs and employees' wellbeing and mental health because of accepting digital technologies.

These constructs are linked to theories as follows:

- Performance expectancy (PE): This construct, defined by Venkatesh et al. (2003), refers to individuals' belief in the system or technology's ability to enhance their job performance.
- Effort expectancy (EE): This construct, also defined by Venkatesh et al. (2003), refers to the ease of using the system.
- Social influence (SI): This construct captures the influence of influential people's views regarding the use and importance of technology.
- Facilitating conditions (FC): This construct represents the perception of the technical infrastructure supporting technology utilisation.
- Hedonic motivation (HM): This construct refers to the pleasure of using a system and is associated with positive emotional experiences with technology.
- Habit (HA): This construct represents the degree of automatic behaviour performance.
- Employee mental health (MH): This construct represents the psychological state and emotional well-being of individuals in the workplace.
- Employee wellbeing (WB): This construct represents the holistic state of comfort, health, and happiness experienced by individuals within the work environment.

The research instrument is attached as Appendix B.

3.8 Procedure for data collection

There are several modes of data collection in research, including participant observation or ethnography, interviews (conducted face-to-face, over the telephone, or through the Internet), self-administered questionnaires (such as mail/postal surveys, group-administered surveys, and online surveys conducted via email or the Internet), focus group discussions, and examination of documents Neuman (2014).

For this study, an online questionnaire (a web survey) was utilised using the Qualtrics platform and the data collected was from employees of financial services organisations in South Africa. Once designed, the link that Qualtrics generated was included in emails sent to a known list of people within the researchers contact list who completed the survey and were also requested to forward the link to their networks. In addition, a message on LinkedIn was generated to connections of the researcher that worked in Financial Services in South Africa. These individuals also forwarded the link to their connections in South Africa. Qualtrics was updated automatically as the respondents answered the questionnaire and the results were stored.

3.9 Data analysis strategies and interpretation

In quantitative research, data processing involves transforming the collected information into a usable form, typically preparing variables for quantification (Bryman, 2012). Neuman (2014) highlights that data processing consists of several steps, including assessing the raw data's relevance to the hypotheses, organising it into a suitable format for computer entry, visually presenting the data (such as through graphs) to summarise their characteristics, and providing theoretical interpretations of the findings. However, before these steps can be undertaken, the raw data are often disorganised, may contain errors and missing values, and require transformation for analysis. This data preparation process involved three tasks: (1) coding, (2) entering the data into a computer, and (3) cleaning the data (Neuman, 2014). Results from the analysis were guided by the hypotheses formulated. Analysis of data began with sample characteristics, followed by reliability analysis, exploratory factor analysis (EFA), descriptive analysis, correlation analysis, confirmatory factor analysis, and then structural equation modelling was conducted to test the hypotheses.

3.10 Quality Assurance

3.10.1 *Internal validity*

Construct and discriminant validity

Construct validity indicates the quality of a research instrument in measuring its intended purpose, and it relies on statistical procedures to determine the contribution of each construct to the total observed variance in a phenomenon (Cooper, 2014). This study used EFA and CFA to test for construct validity, ensuring that the questionnaire effectively measured the constructs used in the study,

Discriminant validity refers to the extent to which scores on a scale do not correlate with scores from scales designed to measure different constructs (Cooper, 2014). Correlations between the various constructs were measured in the questionnaire to assess discriminant validity. Low to moderate correlations between the constructs indicate that the questionnaire effectively distinguishes between the intended constructs and unrelated constructs, thereby providing evidence for discriminant validity.

3.10.2 *Reliability*

Reliability refers to the extent to which a research instrument consistently produces consistent and accurate results (Field, 2018). When a research tool is considered reliable, it is stable, predictable, and consistent in its measurements. In other words, if the instrument is used repeatedly under the same conditions, it should yield the same or similar results. Moser and Kalton (1989) describe reliability as the ability of a scale or test to provide consistent outcomes when administered multiple times in unchanged circumstances (Moser & Kalton, 1989).

Reliability of the measurement scale was assessed, employing Cronbach’s alpha measure of internal consistency. Cronbach’s alpha for each scale was computed using SPPS V26. To ensure good internal consistency (Field, 2018), the Cronbach's alpha values should exceed the recommended threshold of 0.7 to confirm that the measurement scales are reliable and consistent, enhancing the credibility of the collected data for subsequent analyses and interpretations.

Scales used in this study include technology adoption (TA), performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), Habit (HA), employee wellbeing (WB) as well as employee mental health (MH).

3.11 Ethical considerations

Ethical issues were considered at each step of the design and implementation of research, which required the balance between the quest for scientific knowledge and the rights of the subjects being studied.

A participant information sheet requesting consent and informed the participants of the following:

- The data collected during this study would be retained for one year, after which it was securely deleted. Access to this data was exclusively granted to the principal researcher.
- As part of the research process, it was necessary to collect certain personal information from participants, including gender, age, and level of education. Measures were taken to ensure that this information remained confidential and anonymous.
- The decision to participate in the study was entirely voluntary. Individuals were not obligated to participate, and participants could withdraw from the study at any time without penalty. There were no direct benefits for participants who chose to participate in the study, nor would they lose access to any services, benefits, or rights if they opted not to participate. There were no costs associated with participation, and individuals did not receive financial compensation for their involvement.
- This research has culminated in a report, which will be available through the university library's website. Participants who wish to receive a summary of the report could request one, and the researcher will provide it.

This study ensured no harm to the participants, ensuring informed consent and no invasion of privacy or deception involved.

3.12 Chapter conclusion

Chapter 3 discussed the methodology followed in investigating the factors which affect acceptance of digital technologies among employees of financial services organisations in South Africa, and the subsequent impact of this acceptance on the wellbeing and mental health of employees. The chapter revealed that the study followed a positivist philosophy, stressing the use of a quantitative approach to collection and analysis of data. The following chapter focusses on results of the study.

CHAPTER 4. PRESENTATION OF RESULTS

4.1 Introduction

This study examined the impact of the implementation of digital technologies on the mental health and wellbeing of employees within financial services in South Africa. This chapter focuses on analysing data collected from employees of financial services organisations in South Africa. Results from the analysis are then presented guided by the hypotheses formulated. Sample characteristics are discussed in the first section of the chapter. This is followed by reliability analysis, exploratory factor analysis (EFA), descriptive analysis, correlation analysis, confirmatory factor analysis, and then structural equation modelling is conducted to test the hypotheses.

4.2 Sample characteristics

The sample consisted of respondents employed by financial services organisations in South Africa. Employing a convenience sampling method, an online survey was administered to the participants, yielding 210 responses. Subsequently, the collected data underwent a cleaning process to address missing values and incomplete responses. During this process, it was found that 36 responses were incomplete, with participants stopping the survey after completing only the first section on demographic information. These incomplete responses were excluded from the dataset, resulting in a final sample size of 174 valid responses for analysis. Thus, the study utilised a final sample size of 174 respondents. Sample demographic information is discussed in the subsections that follow.

4.2.1 *Demographics*

The sample distribution in this study, as summarised in Table 4-1, reflects gender, age, education, ethnicity, and sector.

	Frequency	Percentage
Gender		
Male	73	42.0%
Female	98	56.3%
Prefer not to say	3	1.7%
Total	**174**	**100.0%**
Age group		
18-25	3	1.7%
26-35	30	17.2%
36-49	89	51.1%
50-65	52	29.9%
Total	**174**	**100%**
Education		
High School	23	13.2%
Undergraduate Degree	35	20.1%
Honours Degree	42	24.1%
Master's degree	41	23.6%
Professional Degree	13	7.5%
Other	20	11.5%
High School	23	13.2%
Total	**174**	**100%**
Ethnic group		
Black African	70	40.2%
White	52	29.9%
Mixed Race	20	11.5%
Indian/Asian	31	17.8%
Other	1	0.6%
Total	**174**	**100%**
Sector		
Banking Services	34	19.5%
Investment and Wealth Management	17	9.8%
Insurance Services	77	44.3%
Financial Advisory and Consulting	13	7.5%
Other	33	19.0%
Total	**174**	**100%**

Table 4-1 Demographics

Data was collected on the gender of respondents to assess the gender representation of the sample. The variable was also crucial to assess how acceptance of digital technologies differ by gender. A gender-diverse composition with 42.0% male, 56.3% female, and 1.7% who preferred not to disclose their gender is reflected. The data indicates a balanced gender distribution, providing a foundation for exploring any gender-related differences in attitudes toward digital technologies within the sampled population.

Respondents stated their age groups, and it was also important to assess whether adoption or acceptance of digital technologies was influenced by age groups. The distribution of respondents across age groups shows diversity. Most of the respondents fall within the 36-49 age group, constituting 51.1% of the sample. The 26-35 age group represents 17.2%, the 50-65 age group accounts for 29.9%, and the 18-25 age group comprises 1.7% of the total respondents. This age-related breakdown is essential for assessing whether the adoption or acceptance of digital technologies varies across different age cohorts within the study's sample of 174 participants. The data suggests a notable presence of individuals in the middle age range, prompting further exploration into potential age-related trends in attitudes toward digital technology adoption in the context of the financial services organisation.

Data was also collected on the highest level of education achieved by a respondent. This variable is important in assessing how acceptance of digital technologies differ by education qualification. The distribution shows that most respondents hold an Honours Degree (24.1%), closely followed by those with a Master's degree (23.6%). Undergraduate Degree holders represent 20.1%, while respondents with a High School education make up 13.2%. Professional Degree holders constitute 7.5%, and 11.5% had other education qualifications. This breakdown is essential for evaluating how acceptance of digital technologies may vary based on education qualifications within the study's sample of 174 participants.

Data on the ethnic group of respondents was collected only for purposes of assessing the representativity of the sample. Results show that most respondents were Black African, constituting 40.2% of the total sample. White respondents make up 29.9%, while individuals from Mixed Race backgrounds represent 11.5%. Those identifying as Indian/Asian account for 17.8%, and a small percentage falls into the 'Other' category at 0.6%. This breakdown indicates a diverse representation across ethnic groups within the sample.

The study collected data from respondents within the financial services sector in which they operate. Results show that most respondents are engaged in Insurance Services, constituting 44.3% of the total sample. Banking Services represent 19.5%, while Financial Advisory and Consulting make up 7.5%. Investment and Wealth Management account for 9.8%, and the 'Other' category comprises 19.0%.

4.3 Reliability analysis

Reliability of the measurement scale was assessed, employing Cronbach’s alpha measure of internal consistent. Cronbach’s alpha for each scale was computed using SPPS V26 as shown in Table 4-2. Scales used in this study include technology adoption (TA), performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), hedonic motivation (HM), Habit (HA), employee wellbeing (WB) and employee mental health (MH).

Scale	Number of items	Items deleted	Cronbach’s alpha
TA	4	0	0.891
PE	2	0	0.962
EE	2	0	0.843
SI	2	0	0.509
FC	2	0	0.796
HM	2	0	0.911
HA	2	0	0.912
WB	3	0	0.810
MH	3	0	0.900

Table 4-2 Reliability analysis

The results presented in Table 4-2 show robust internal consistency for the scales. Across all scales, except SI, the Cronbach's alpha values exceeded the recommended threshold of 0.7, indicating good internal consistency (Field, 2018). Specifically, technology adoption achieved an alpha of 0.891, performance expectancy scored 0.962, effort expectancy attained 0.843, facilitating conditions scored 0.796, hedonic motivation achieved 0.911, habit scored 0.912, employee wellbeing reached 0.810, and employee mental health achieved 0.900. These high alpha values suggest that the measurement scales are reliable and consistent, enhancing the credibility of the collected data for subsequent analyses and interpretations. No items were removed following analysis of alpha before and after potential deletion of an item.

However, results show that the SI scale has a Cronbach's alpha of 0.509, falling below the commonly accepted threshold of 0.7 for internal consistency. However, evidence suggests that low Cronbach's alpha values of at least 0.4 can be accepted as they do not necessarily suggest that there is a problem with the scale but could be due to the low number of items in the scale or the nature of the construct (Tavakol, M., & Dennick, 2011; Kılıç, 2016). Therefore, the SI scale was used for analysis in this study. Further analysis was conducted, examining the factor structure, and theoretical foundations of the SI construct, thus supporting the continued use of the measurement scale.

4.4 Exploratory Factor Analysis (EFA)

EFA was conducted to uncover the underlying factor structure of the measured constructs. The primary purpose was to identify patterns and relationships among the observed variables, allowing for a more nuanced understanding of the acceptance of digital technologies and its associated factors within the financial services sector.

Before proceeding with the EFA, the adequacy of the sample was assessed using the Kaiser-Meyer-Olkin (KMO) measure and the Bartlett Test of Sphericity. The KMO test evaluates whether the variables in the dataset are suitable for factor analysis by measuring the proportion of variance among variables that might be common variance (Field, 2018). The Bartlett Test of Sphericity assesses whether correlations between variables are significantly different from an identity matrix (Field, 2018).

The results of the sample adequacy tests are presented in Table 4-3, providing insights into the suitability of the dataset for factor analysis.

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.907
Bartlett's Test of Sphericity	Approx. Chi-Square	3282.406
	Df	231
	Sig.	.000

Table 4-3 Sample adequacy test

The results of the sample adequacy test, as shown in Table 4-3, indicate that the sample size was well-suited for factor analysis. The KMO measure of sampling adequacy is 0.907, surpassing the commonly accepted threshold of 0.5 (Field, 2018). This suggests a high degree of shared variance among the variables, indicating that the dataset provides ample information for factor extraction.

Furthermore, the Bartlett's Test of Sphericity yielded a significant result *(Chi-Square =3282.406, df = 231, Sig. < 0.001).* The significant chi-square value indicates that the observed variables in the dataset are not an identity matrix, supporting the presence of significant relationships among them. Together, these results suggest that the sample size is adequate for conducting exploratory factor analysis, providing confidence in the reliability of subsequent factor extraction and interpretation.

The next step in the analysis involved factor extraction, which was carried out based on the eigenvalue criterion. Eigenvalues represent the amount of variance explained by each factor (Field, 2018). In this study, factors with eigenvalues greater than 1 were retained, a common criterion for determining the number of factors to extract (Field, 2018). Principal Components Analysis (PCA) was chosen as the extraction method, aiming to capture the maximum variance in the dataset. Using PCA, 9 components or factors were retained in this study, aligning with the eigenvalue criterion. Total variance explained by the components extracted is shown in Table 4-4.

Component	Rotation Sums of Squared Loadings		
	Total	% of Variance	Cumulative %
1	6.203	28.195	28.195
2	3.533	16.059	44.254
3	2.369	10.768	55.022
4	1.745	7.934	62.956
5	1.132	5.148	68.104
6	1.128	5.126	73.230
7	1.082	4.919	78.149
8	1.070	4.861	83.010
9	.901	4.093	87.104
Extraction Method: Principal Component Analysis.			

Table 4-4 Total Variance Explained

The extracted factors collectively about 87.1% of the total variance in the dataset. This suggests that the identified factors effectively capture and represent a significant portion of the variability present in the measured variables. The cumulative variance explained provides confidence in the comprehensiveness of the factor extraction process.

		Component							
	1	2	3	4	5	6	7	8	9
PE1			.896						
PE2			.883						
EE1				.878					
EE2				.701					
SI1						.927			
SI2						.744			
FC1									.631
FC2									.764
TA1	.775								
TA2	.658								
TA3	.761								
TA4	.662								
HM1					.873				
HM2					.877				
HA1							.614		

HA2							.669		
WB1								.824	
WB2								.710	
WB3								.426	
MH1		.898							
MH2		.909							
MH3		.887							
	Extraction Method: Principal Component Analysis. Rotation Method: Varimax with Kaiser Normalization.								
	a. Rotation converged in 8 iterations.								

Table 4-5 Rotated Component Matrix

Factor rotation is a technique employed after factor extraction to simplify the interpretation of the underlying structure of variables. In this study, the Varimax rotation method with Kaiser Normalisation was utilised. Varimax aims to maximise the variance of the squared loadings for each factor, resulting in a clearer and more interpretable factor structure (Field, 2018). The rotated component matrix in Table 4-5 shows the factor loadings of each item after rotation. Factor loadings represent the strength and direction of the relationship between each variable and the identified factors. A loading above 0.4 is typically considered significant and indicates a meaningful association.

In this analysis, no cross loadings were observed, ensuring that each item primarily loaded on one factor. Factor loadings above 0.4 were retained, contributing to the convergent validity of the factors. All items had factor loadings above this threshold, indicating a strong association with their respective factors and affirming the convergent validity of the measurement model. With the factor structure confirmed, composite scales were calculated. Composite scales involve summing or averaging the scores of the individual items that load on a specific factor, resulting in a single score for each factor. These composite scales were for correlation and descriptive statistics, providing a consolidated measure for each underlying construct identified through EFA.

4.5 Descriptive statistics

Descriptive statistics provide an overview of the data distribution and the respondents' perceptions on the 7-point Likert scale (1 = strongly disagree, 4 = neutral, 7 = strongly agree). Descriptive statistics, such as mean scores and standard deviations, offer insights into the central tendency and variability of responses, helping to understand the level of agreement or disagreement with the measured constructs.

Additionally, skewness and kurtosis values are crucial for assessing the normality of the data distribution. According to George and Mallery (2019), skewness values falling between -2 and +2 and kurtosis values between -7 and +7 are considered acceptable for proving normal univariate distribution. Values within these ranges indicate a roughly symmetrical and normally distributed dataset (Hair et al., 2019). If skewness and kurtosis fall within the acceptable ranges, it suggests that parametric statistical tests (which assume normality) can be reliably applied.

	N	Minimum	Maximum	Mean	Std. Deviation	Skewness		Kurtosis	
	Statistic	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Std. Error
TA	174	1.00	7.00	6.24	.920	-3.30	.184	15.39	.366
PE	174	1.00	7.00	6.16	1.37	-2.80	.184	8.01	.366
EE	174	1.00	6.50	5.39	1.17	-2.35	.184	5.64	.366
SI	174	1.00	7.00	5.46	.998	-2.01	.184	5.86	.366
FC	174	1.00	7.00	5.99	1.10	-2.30	.184	7.27	.366
HM	174	1.00	7.00	6.12	.99	-2.57	.184	10.57	.366
HA	174	1.00	7.00	5.91	1.09	-2.02	.184	6.51	.366
WB	174	1.00	7.00	5.36	1.34	-1.19	.184	1.24	.366
MH	174	1.00	7.00	4.92	1.42	-.72	.184	-.14	.366

Table 4-6 Descriptive statistics

The results reveal that, on average, respondents demonstrated a high level of agreement with various constructs related to the acceptance of digital technologies within the financial services sector. Notably, the scales for technology adoption (TA), performance expectancy (PE), and hedonic motivation

(HM) exhibited particularly high mean scores of 6.24, 6.16, and 6.12, respectively. These high mean scores suggest a strong consensus among respondents in favour of technology adoption, emphasising the perceived performance benefits, and acknowledging the hedonic aspects related to the use of digital technologies in their work environment. Social influence (SI), facilitating conditions (FC) and habit (HA) also had relatively high mean scores of 5.46, 5.99 and 5.91, respectively, indicating a favourable disposition towards social influence, the ease of use and habitual nature of incorporating digital technologies in the workplace.

In terms of normality, the skewness and kurtosis values provide insights into the shape and distribution of responses for each construct. Skewness values ranging from -3.30 to -0.72 generally indicate negatively skewed distributions, suggesting a concentration of responses towards the higher end of the Likert scale. The kurtosis values, mostly within acceptable ranges, reflect the degree of tails in the distributions. Notably, WB and MH demonstrated relatively normal distributions with skewness and kurtosis values within the acceptable range, providing confidence in the assumption of normality for these constructs. Overall, the results suggest that, while some constructs exhibit deviations from normality, most of the scales align with the assumed distribution, enhancing the reliability of subsequent statistical analyses. Given the large sample size in this study, the Central Limit Theorem (CLT) becomes particularly relevant in assessing the normality of the data. The CLT posits that, irrespective of the underlying distribution of individual variables, the distribution of sample means tends to follow a normal distribution as the sample size increases (Hair et al., 2019).

4.6 Inferential statistics

The study sought to assess whether differences in acceptance of digital technologies are explained by differences in gender and age. One way analysis of variance (ANOVA) was conducted to test whether the means for technology acceptance are significantly different across groups.

4.6.1 Gender and acceptance of digital technologies

The results from the one-way ANOVA examining the relationship between gender and acceptance of digital technologies (TA) reveal marginal differences across gender categories.

Gender	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	95% Confidence Interval for Mean Upper Bound
Male	73	6.29	0.95	0.11	6.07	6.52
Female	98	6.18	0.91	0.09	6.00	6.36
Prefer not to say	3	6.83	0.14	0.08	6.47	7.19
Total	**174**	**6.24**	**0.92**	**0.07**	**6.10**	**6.38**

Table 4-7 Descriptives: Gender and TA

TA	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	1.61	2	.806	.951	.388
Within Groups	144.93	171	.848		
Total	146.55	173			

Table 4-8 Gender and TA

Descriptive statistics indicate that, on average, male respondents reported a slightly higher mean TA score *(M = 6.29*) compared to female respondents *(M = 6.18),* with those who preferred not to disclose their gender showing the highest mean score (M = *6.83).* However, the confidence intervals overlap, suggesting limited practical significance. The ANOVA results further support this observation, indicating that the differences in means across gender categories are not statistically significant (*F = 0.951, p = 0.388).* Therefore, based on these findings, gender is not a significant predictor of differences in the acceptance of digital technologies in the studied sample.

4.6.2 Age and acceptance of digital technologies

The results of the one-way ANOVA examining the relationship between age groups and acceptance of digital technologies show minor variations in mean TA scores across different age categories.

Age group	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean	
					Lower Bound	Upper Bound
18-25	3	6.08	0.38	0.22	5.13	7.03
26-35	30	6.04	1.54	0.28	5.47	6.62
36-49	89	6.35	0.57	0.06	6.23	6.47
50-65	52	6.17	0.95	0.13	5.91	6.44
Total	174	6.24	0.92	0.07	6.10	6.38

Table 4-9 Descriptives: Age and TA

TA					
	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	2.59	3	.862	1.018	.386
Within Groups	143.96	170	.847		
Total	146.55	173			

Table 4-10 Age and TA

Descriptive statistics show that respondents in the 36-49 age group reported the highest mean TA score (M = 6.35), followed by those aged 50-65 (M = 6.17), 26-35 age group (M = 6.04), and the 18-25 age group (M = 6.08). However, the confidence intervals overlap, indicating limited practical significance.

The ANOVA results support these observations, showing that the differences in mean TA scores across age groups are not statistically significant (*$F = 1.018$, $p = 0.386$*). Therefore, based on these findings, age is not a significant predictor of differences in the acceptance of digital technologies in the studied sample.

4.7 Correlation analysis

Correlation analysis was conducted to assess the strengths of the relationships among the variables. Results in Table 4-11 show that the dependent variable (TA) is significantly correlated with explanator variables (PE, EE, SI, FC, HM, and HA), all with medium to strong positive correlations. In addition, TA is significantly correlated with WB and MH, all with positive correlations. Importantly, correlations among explanatory variables are all less than 0.8, implying that variables are not highly correlated, thus indicating no multicollinearity issues (Hair et al., 2019).

Construct		TA	PE	EE	SI	FC	HM	HA	WB	MH
TA	Pearson Correlation	1								
PE	Pearson Correlation	.597**	1							
EE	Pearson Correlation	.561**	.606**	1						
SI	Pearson Correlation	.649**	.455**	.491**	1					
FC	Pearson Correlation	.709**	.530**	.634**	.623**	1				
HM	Pearson Correlation	.733**	.493**	.471**	.537**	.727**	1			
HA	Pearson Correlation	.755**	.420**	.558**	.571**	.675**	.754**	1		
WB	Pearson Correlation	.392**	.218**	.281**	.439**	.335**	.323**	.415**	1	
MH	Pearson Correlation	.214**	.115	.164*	.322**	.253**	.179*	.213**	.688**	1
**. Correlation is significant at the 0.01 level (2-tailed).										
*. Correlation is significant at the 0.05 level (2-tailed).										

Table 4-11 Correlations

4.8 Confirmatory Factor Analysis (CFA)

Following the EFA that identified nine factors encompassing TA, PE, EE, SI, FC, HM, HA, WB and MH, a confirmatory factor analysis was conducted using AMOS 26. The objective of CFA was to validate the factor structure obtained through

EFA and assess how well the hypothesised measurement model aligns with the observed data. The CFA model was specified based on the identified factors, and its fit was evaluated using various fit indices. The Chi-square (CMIN) statistic, a traditional measure of model fit, was expected to be insignificant, indicating that the hypothesised model does not significantly differ from the observed data (Hair et al., 2019). Additionally, attention was given to other fit indices, including the Goodness of Fit Index (GFI), Tucker-Lewis Index (TLI), Comparative Fit Index (CFI), and Root Mean Square Error of Approximation (RMSEA), each with specific threshold conditions for indicating an acceptable fit (Field, 2018). Table 4-12 summarises CFA model fit measures.

CMIN					
Model	**NPAR**	**CMIN**	**DF**	**P**	**CMIN/DF**
Default model	83	269.136	170	0	1.583
Saturated model	253	0	0		
Independence model	22	3445.033	231	0	14.914
FIT INDEX	**GFI**	**TLI**	**CFI**	**RMSEA**	
Value	0.901	0.958	0.969	0.058	

Table 4-12 CFA model fit measures

Results show that the Chi-square degrees of freedom (CMIN/DF= 1.583), which is less than the required threshold of 3 (Field, 2018). However, the significant Chi-square suggests the hypothesised model significantly differs from the data ($p<.001$). However, the significance of the Chi-square test is contingent on the sample size, and in large samples, it tends to be sensitive, often resulting in statistical significance (Hair et al., 2019). Therefore, this study complemented the Chi-square test with fit indices that account for sample size. GFI, TLI, and CFI values closer to 1 indicate better fit, with values exceeding 0.90 considered acceptable. Similarly, RMSEA values below 0.08 are generally indicative of an adequate fit. Results in table 4-12 show that the GFI, TLI and CFI index are above 0.9, indicative of good fit (Hair et al., 2019). In addition, RMSEA is within acceptable range of good fit. Therefore, the CFA was considered a good fit, implying that the was appropriate in representing the underlying factor structure identified in the EFA.

Convergent validity was analysed using average variance extracted. Results are summarised in the following table.

Observed variable		Latent variable	St. Estimate	AVE	Composite reliability	p
PE1	<---	PE_	0.954	0.941	0.970	p<.001
PE2	<---	PE_	0.986			p<.001
EE1	<---	EE_	0.730	0.740	0.848	p<.001
EE2	<---	EE_	0.973			p<.001
FC1	<---	FC_	0.867	0.672	0.803	p<.001
FC2	<---	FC_	0.770			p<.001
HM1	<---	HM_	0.937	0.839	0.912	p<.001
HM2	<---	HM_	0.894			p<.001
H1	<---	HA_	0.894	0.840	0.913	p<.001
H2	<---	HA_	0.938			p<.001
WB1	<---	WB_	0.694	0.595	0.815	p<.001
WB2	<---	WB_	0.797			p<.001
WB3	<---	WB_	0.818			p<.001
MH1	<---	MH_	0.938	0.749	0.899	p<.001
MH2	<---	MH_	0.881			p<.001
MH3	<---	MH_	0.769			p<.001
SI1	<---	SI_	0.416	0.423	0.570	p<.001
SI2	<---	SI_	0.820			p<.001
TA4	<---	TA_	0.753	0.677	0.893	p<.001
TA3	<---	TA_	0.830			p<.001
TA2	<---	TA_	0.811			p<.001
TA1	<---	TA_	0.891			p<.001

Table 4-13 Convergent validity

Table 4-13 shows CFA for the observed variables loading onto their respective latent constructs. Convergent validity was assessed through the Average Variance Extracted (AVE) and Composite Reliability (CR) measures. AVE values reflect the amount of variance captured by the latent construct relative to measurement error. In this case, except for the factor SI, AVE ranges from 0.633 to 0.940. Generally, AVE values exceeding 0.50 are considered acceptable, suggesting satisfactory convergent validity (Field, 2018). Additionally, Composite Reliability values, which measure the internal consistency of the constructs, range from 0.803 to 0.969, surpassing the recommended threshold of 0.70. The standardised estimates (Std. Estimate) further emphasise the strength and direction of the relationships between the observed variables and their respective latent constructs. Notably, all standardised estimates are statistically significant ($p < .001$), indicating robust relationships. This assessment provides evidence for the convergent validity of the latent constructs, as supported by high AVE values, satisfactory composite reliability, and significant standardised estimates, affirming the measurement model's reliability and the consistency of relationships within the specified theoretical framework.

The study continued to use the SI factor despite low AVE and CR since it is a core variable in the UTAUT, the theoretical model adopted in this study.

	TA	PE	EE	SI	FC	HM	HA	WB	MH
TA	0.823								
PE	.597	0.970							
EE	.561	.606	0.860						
SI	.649	.455	.491	0.650					
FC	.709	.530	.634	.623	0.820				
HM	.733	.493	.471	.537	.727	0.916			
HA	.755	.420	.558	.571	.675	.754	0.916		
WB	.392	.218	.281	.439	.335	.323	.415	0.772	
MH	.214	.115	.164	.322	.253	.179	.213	.688	0.866

Table 4-14 Matrix of correlations

The matrix of correlations in Table 4-14 shows the pairwise correlations between latent constructs (TA, PE, EE, SI, FC, HM, HA, WB, MH). Each diagonal element represents the square root of the average variance extracted for the corresponding construct, which is a measure of the variance captured by that construct relative to measurement error.

To assess discriminant validity, the off-diagonal correlations are compared with the square roots of AVE values. According to the Fornell-Larcker criterion, discriminant validity is supported when the square root of AVE for a construct is greater than the construct's correlations with other constructs (Rasoolimanesh, 2021). In this case, all the diagonal elements (square roots of AVE) are greater than the correlations in their respective rows and columns. This indicates that each latent variable shares less variance with other constructs than the variance it captures internally. Therefore, based on this analysis, discriminant validity was established among the latent constructs in the study.

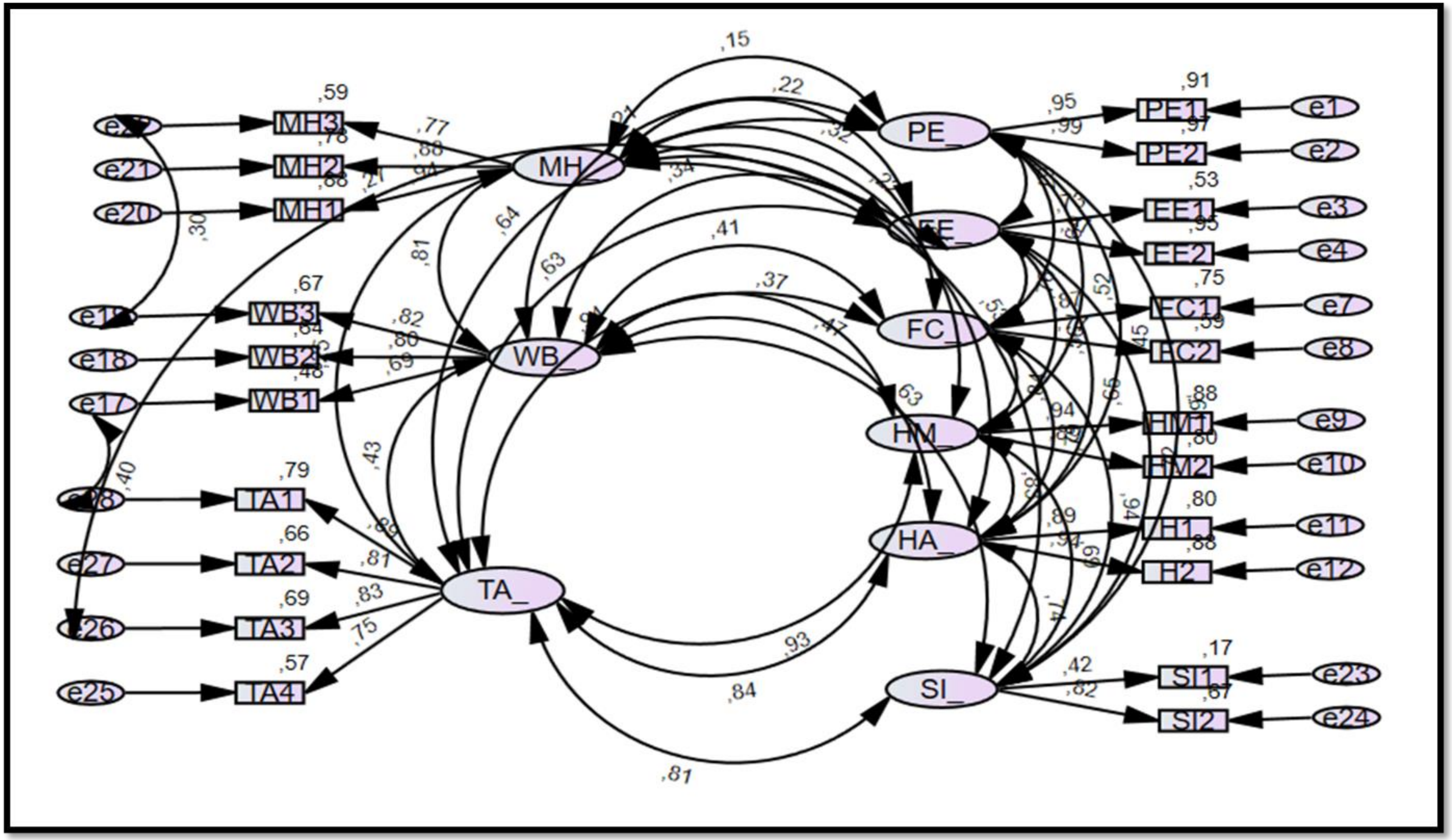
PE_
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Figure 4-1 Measurement model

The measurement model shows the relationships among latent variables and their observables variables. The standardised factor loadings are shown, and the arrows shows various relationships. Some unobservable variables were allowed to covary to improve model fit, guided by modification indices.

4.9 Structural Equation Modelling (SEM)

With both convergent and discriminant validity established through rigorous assessment of the measurement model, the study proceeded to employ structural equation modelling to examine the relationships among the confirmed constructs. This stage enables the exploration of the underlying structural pathways, providing insights into the complex interplay between latent variables. The structural equation model serves as a powerful tool to assess the hypothesised connections and answer the research questions posed in this study.

The SEM was assessed for model fit as summarised in Table 4-15:

CMIN					
Model	**NPAR**	**CMIN**	**DF**	**P**	**CMIN/DF**
Default model	64	521.412	189	0	2.759
Saturated model	253	0	0		
Independence model	22	3445.033	231	0	14.914
FIT INDEX	**GFI**	**TLI**	**CFI**	**RMSEA**	
Value	0.831	0.904	0.923	0.071	

Table 4-15 Structural Equation Model

Table 4-15 shows that the chi-square test statistic (CMIN) is 521.412 with 189 degrees of freedom, resulting in a ratio of 2.759. While the CMIN/DF is statistically significant, it is essential to consider alternative fit indices for a comprehensive assessment. The CFI, TLI, and GFI reported values of 0.923, 0.904, and 0.831, respectively. These indices indicate a reasonable fit, with the CFI and TLI with the recommended threshold of 0.90. Additionally, the RMSEA has a value of 0.071, falling within an acceptable range. Therefore, the combined evidence from fit indices suggests that the SEM model adequately represents the underlying relationships among the validated constructs in this study.

Table 4-16 presents a summary of the SEM estimates, showing the relationships among the constructs (dependent variable (DV) and independent variables (IV), and providing solutions to the hypotheses formulated.

DV		IV	Unst. estimate (B)	S.E.	C.R.	St. estimate (β)	P
TA_	<---	PE_	0.106	0.031	3.458	0.206**	p<.001
TA_	<---	EE_	-0.084	0.072	-1.167	-0.092	0.243
TA_	<---	FC_	0.425	0.121	3.507	0.535**	p<.001
TA_	<---	HM_	0.294	0.111	2.647	0.410**	0.008
TA_	<---	HA_	0.044	0.086	0.518	0.058	0.605
TA_	<---	SI_	0.249	0.094	2.653	0.266**	0.008
MH_	<---	TA_	0.53	0.162	3.268	0.260**	p<.001
WB_	<---	TA_	0.679	0.155	4.39	0.407**	p<.001
**Coefficient is significant at 0.01 level							

Table 4-16 Structural Parameter Estimates

The path diagram of the estimated SEM is shown Figure 4.2.

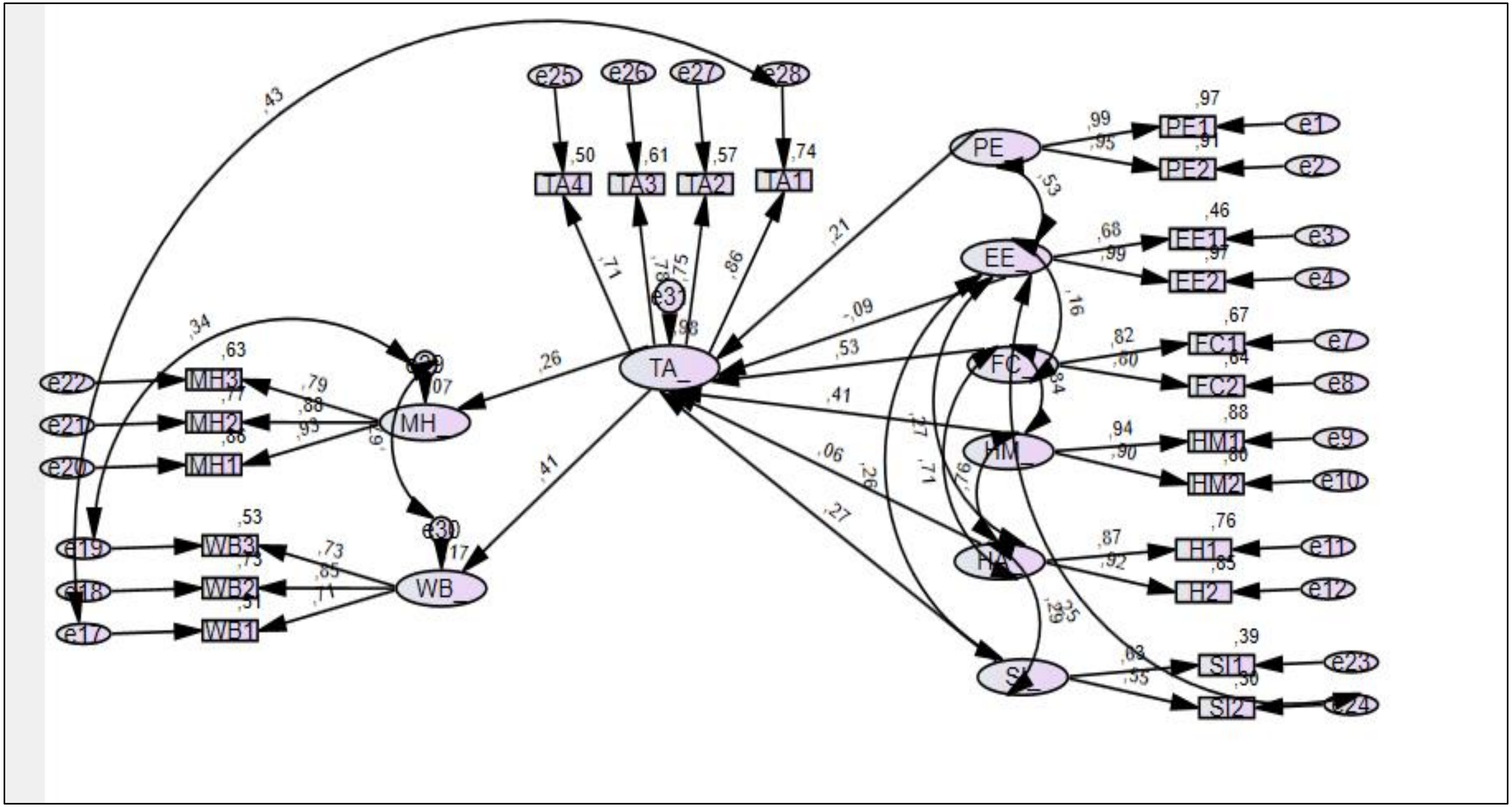

Figure 4-2 Structural Parameter Estimates Path Diagram

The final structural equation model revealed significant predictors of digital technology acceptance within the financial services industry in South Africa and impact on employee wellbeing and employee mental health. Notably, performance expectancy (PE) has a positive and statistically significant relationship with digital technology acceptance (TA) (*β =0.206, p < .001*). Facilitating conditions (FC) also has a positive and statistically coefficient (*β = 0.535, p < .001).* Hedonic motivation (HM) contributed positively to digital technology acceptance (*β =0.410, p<.01*). Additionally, results show that social influence (SI) positively influences digital technology acceptance (*β=0.266, p<.01)*. These findings highlight the significance of perceived performance, facilitating conditions, hedonic motivations, and social influence as key determinants of digital technology acceptance in the financial services sector. Furthermore, employee mental health (MH) and employee wellbeing (WB) were significantly influenced by digital technology acceptance. Acceptance of digital technologies improves employee mental health (*β=0.26, p < .001)* and improves employee wellbeing (*β=0. 0.407, p < .001)*. Detailed interpretation and implications of these findings will be discussed in Chapter 5.

4.10 Summary of hypotheses

Table 4-17 provides a summary of hypotheses tested in this study, providing details as to whether the hypotheses were supported or not supported.

DV		IV	(β)	P	Hypothesis	Conclusion
TA_	<---	PE_	0.206	P<.001	H1: Performance expectancy positively influences acceptance of digital technologies.	Supported
TA_	<---	EE_	-0.092	0.234	H2: Effort expectancy positively influences acceptance of digital technologies.	Not supported
TA_	<---	FC_	0.535	P<.001	H3: Facilitating conditions positively influences acceptance of digital technologies.	Supported
TA_	<---	HM_	0.41	P<.01	H4: Hedonic motivation positively influences acceptance of digital technologies.	Supported

DV		IV	(β)	P	Hypothesis	Conclusion
TA_	<---	HA_	0.058	0.605	H5: Habit positively influences acceptance of digital technologies.	Not supported
TA_		SI_	0.266	P<.01	H6: Social influence positively influences acceptance of digital technologies	Supported
TA_		SI_	0.266	P<.01	H6: Social influence positively influences acceptance of digital technologies	Supported
MH_	<---	TA_	0.26	P<.001	H7: Acceptance of digital technologies positively influences employee mental health.	Supported
WB_	<---	TA_	0.407	P<.001	H8: Acceptance of digital technologies positively influences employee wellbeing.	Supported.

Table 4-17 Summary of hypotheses

4.11 Summary of the results

This chapter presented results from the analysis of the impact of digital technologies on the mental health and wellbeing of executives and employees within the financial services industry in South Africa. The chapter commenced with an exploration of sample characteristics, followed by reliability analysis, exploratory factor analysis, and descriptive statistics. Inferential statistics revealed that age and gender did not significantly influence technology acceptance. Subsequently, confirmatory factor analysis was undertaken, affirming the robustness of the measurement model. The chapter culminated in the estimation of a structural equation model, revealing key predictors of digital technology acceptance. Notably, performance expectancy, facilitating conditions, social influence and hedonic motivation emerged as significant contributors to technology acceptance. Furthermore, the SEM highlighted the intricate relationships between technology acceptance and employee mental health, as well as employee wellbeing. These results are discussed in detail in Chapter 5.

CHAPTER 5. DISCUSSION OF THE RESULTS

5.1 Introduction

This study focused on the impact of digital technologies on employees' mental health and wellbeing in financial services organisation in South Africa. Results from the analysis of data collected were presented in the preceding chapter. In this chapter, focus is on discussing the results, comparing them with findings from previous studies and the broader literature. The results were discussed per each of the stated hypotheses.

5.2 Discussion pertaining to Hypothesis 1

Hypothesis 1(H1): Favourable perceptions of performance expectancy positively influence acceptance of digital technologies.

This study hypothesised that acceptance of digital technologies would be positively influenced by favourable perceptions of performance expectancy. Results confirmed the prediction of the UTAUT, showing that there was a significant and positive relationship between performance expectance and acceptance of digital technologies. This finding implies that employees within financial organisations are more likely to accept and integrate digital technologies into their work processes when they perceive these technologies as enhancing their performance. This aligns with the sector's continuous reliance on technological advancements to improve efficiency, accuracy, and overall performance (Hassan et al., 2022).

This result resonates with existing studies which found that performance expectancy was instrumental in shaping an individual's behavioural intention to adopt a technology (Venkatesh et al. 2003; Shaikh et al., 2021; Nikolopoulou et al., 2021, Xie et al., 2021). It is noteworthy that financial services organisations are profit-driven entities, placing a high premium on employee performance. The imperative for high performance serves as a catalyst, motivating employees to embrace technologies that enhance their capabilities. Consequently, this not only aids the organisation in accomplishing its objectives but also empowers employees to attain their performance targets. The symbiotic relationship between technological adoption, organisational goals, and individual performance highlights the strategic alignment of technology utilisation with the overarching mission of financial service organisations (Hassan et al. 2022; Hassan et al. 2023).

From a behavioural standpoint, these findings reinforce the importance of performance expectancy as a key determinant in the acceptance of digital technologies within the financial services sector. Therefore, enhancing performance expectancy through the perceived usefulness and value of digital technologies is crucial for promoting employees' acceptance and adoption of digital technologies. Financial service organisations can therefore leverage these insights by highlighting the performance-enhancing features of the digital technologies, providing clear communication on their benefits, and offering training programs to showcase the positive impact on job performance.

5.3 Discussion pertaining to Hypothesis 2

Hypothesis 2 (H2): Favourable perception of effort expectancy positively influences acceptance of digital technologies.

This study investigated how perceptions of effort expectancy influence acceptance of digital technologies. It was hypothesised that effort expectancy would positively influence acceptance of digital technologies in financial services organisations. However, to the contrary, results showed no significant influence of effort expectance on the acceptance of digital technologies. This result is contrary to the predictions of the UTAUT and contradicts prior studies which found that effort expectancy was a significant predictor of acceptance to use digital technologies (Batucan et al., 2022; Fedorko et al., 2021; Chatterjee et al., 2021). The UTAUT posits that users are more likely to accept and use a technology if they perceive it to be easy to use, reducing the effort required for adoption (Venkatesh et al., 2003).

However, the result is not surprising as there are also a few studies which have found an insignificant relationship between effort expectancy and acceptance and use of technologies in different contexts (Ramírez-Correa et al., 2023; Batucan et al., 2022). Therefore, in certain contexts, the perceived ease of use of a system may not significantly impact the intention to use technology, and other factors may take precedence. The financial services sector often involves complex and intricate tasks and in such an environment, other factors such as the perceived benefits of technology in enhancing performance or the organisational culture may overshadow the perceived ease of use (Xie et al., 2021). Employees in financial services may prioritise performance-enhancing features over ease of use when evaluating the acceptance of digital technologies.

Therefore, this result suggests that, within financial services organisations, efforts to promote the acceptance of digital technologies should not solely focus on ease of use. Instead, emphasising the performance benefits and addressing potential barriers specific to the financial sector may be more effective in fostering technology adoption.

5.4 Discussion pertaining to Hypothesis 3

Hypothesis 3 (H3): Facilitating conditions positively influences acceptance of digital technologies.

Hypothesis 3 posited that facilitating conditions, encompassing the availability of resources, support, and infrastructure necessary for the adoption and usage of digital technologies within financial services organisations, would positively influence their acceptance. The results from the structural equation modelling provided robust support for this hypothesis, with a significant positive relationship found between facilitating conditions and the acceptance of digital technologies. This result conforms to the predictions of the UTAUT which emphasises the role of facilitating conditions in shaping technology acceptance (Taherdoost, 2018).

This study also expected facilitating conditions to contribute positively to acceptance of digital technologies. Facilitating conditions encompass the external factors that make it easier for individuals to adopt and use technology

(Venkatesh et al., 2003). A positive perception of these conditions enhances the likelihood of technology acceptance and successful implementation within an organisation.

The significance of facilitating conditions in influencing technology acceptance has been substantiated by previous research (Batucan et al., 2022; Peñarroja et al., 2019; Taherdoost, 2018; Sukendro et al., 2020). The result is important because it affirms the importance of ensuring that financial services organisations provide the necessary support systems and resources to facilitate the seamless adoption of digital technologies by their employees. Such facilitating conditions may include adequate training programs, accessible technical support, well-designed infrastructure, and a culture that encourages and supports technological innovation (Shaikh et al., 2021). When employees perceive an environment conducive to utilising digital technologies, they are more likely to embrace and incorporate these technologies into their daily work routines. This is particularly relevant in the rapidly evolving landscape of the financial services sector, where staying technologically competitive is an imperative (Singh et al., 2020).

The implication of this result is that organisations looking to enhance the acceptance of digital technologies should not only focus on individual perceptions but also invest in creating a supportive and resource-rich environment. This approach aligns with the broader understanding that successful technology adoption is not solely dependent on individual beliefs and attitudes but is intricately tied to the organisational ecosystem.

5.5 Discussion pertaining to Hypothesis 4

Hypothesis 4 (H4): Hedonic motivation positively influences acceptance of digital technologies.

The fourth hypothesis focused on the influence of hedonic motivation on the acceptance of digital technologies in financial services organisations. Results provided support for the hypothesis, revealing that that hedonic motivation was positively correlated with acceptance of digital technologies.

The result aligns with the broader literature, emphasising the role of hedonic motivation as a significant influencer in technology acceptance (Taherdoost, 2018; Tamilmani et al., 2019; Hartelina et al., 2021). In addition, the positive correlation found in this study supports and extends these findings to the financial services sector, indicating that hedonic motivation plays a crucial role in influencing the acceptance of digital technologies in various organisational settings (Venkatesh et al., 2012; Nikolopoulou et al., 2021).

Schomakers et al. (2022) extended the UTAUT2 model to explain user acceptance of lifestyle and therapy mobile health apps. The study highlighted that hedonic motivation emerged as a strong predictor in the context of mobile health app acceptance. This underscores the broader applicability of hedonic motivation as an affective factor influencing the intention to use various digital applications, including those related to health and lifestyle. Nikolopoulou et al. (2021) further contributed to the understanding of hedonic motivation by demonstrating its significance in predicting teachers' intention to use mobile internet. The positive correlation found in this study resonates with their findings, supporting the notion that hedonic motivation is a relevant factor not only in consumer-oriented technologies but also in professional contexts such as education and, as revealed in this study, within financial services organisations.

Hedonic motivation shapes technology acceptance by tapping into individuals' emotional and experiential aspects. When users find pleasure, enjoyment, or intrinsic satisfaction in using a technology, their hedonic motivation positively influences their acceptance of that technology (Tamilmani et al., 2019). This emotional connection enhances the perceived value of the technology, fostering a more favourable attitude and intention to use. The enjoyment derived from the interactive and pleasurable features of the technology, such as user-friendly interfaces, engaging functionalities, or entertaining elements, contributes significantly to its overall acceptance (Hartelina et al., 2021).

Practically, the result suggests that organisations within the financial services sector may benefit from incorporating elements that appeal to employees' affective experiences when implementing digital technologies. This could include designing user interfaces that evoke positive emotions, incorporating gamification elements, or highlighting the enjoyable aspects of using the technology.

5.6 Discussion pertaining to Hypothesis 5

Hypothesis 5 (H5): Social Influence has a positive influence on technology acceptance.

Hypothesis 5 proposed a positive influence of social influence on technology acceptance. Results confirmed that employees' acceptance of digital technologies within financial services organisations was positively influenced by social influence. This result aligns with the predictions of the UTAUT, which acknowledges the impact of social factors on technology adoption. In addition, the positive influence of social influence on technology acceptance mirrors findings in existing studies. Numerous studies have emphasised the role of social influence in shaping individuals' perceptions and decisions regarding technology adoption (Venkatesh et al., 2003; Kulviwat et al., 2009; Alshammari, 2021, Batucan et al., 2022).

The impact of social influence on acceptance and use of digital technologies may manifest through peer recommendations, opinions of influential colleagues, or even organisational culture, creating a network of interactions that contribute to the overall acceptance of digital technologies. In the landscape of South Africa, social media has emerged as a pivotal force in nation-building, offering a unique platform with the transformative potential to bridge longstanding racial, ethnic, and cultural divides (Matema & Kariuki, 2022). This observation underscores the profound impact of social influence on shaping attitudes and behaviours within the societal fabric of the nation. The result of this study hints at a broader societal context, where the influence of social factors extends beyond individual behaviours to contribute significantly to the collective mindset of South African society. It aligns with a broader sentiment evident in Sub-Saharan Africa, where there is a prevailing positive outlook on the internet's impact across various facets, including education, the economy, and interpersonal relationships (Silver & Johnson, 2020).

However, it is essential to acknowledge that social influence can be a double-edged sword. While positive influence can foster technology acceptance, negative social influence or resistance from influential figures may act as barriers to adoption (Kulviwat et al., 2009). Therefore, financial services organisations should recognise the influential role of social interactions in technology adoption and strategically leverage positive social influence. Strategies that promote a positive technology culture, encourage knowledge sharing, and highlight success stories within the organisation can enhance the positive impact of social influence on technology acceptance.

5.7 Discussion pertaining to Hypothesis 6

Hypothesis 6 (H6): Habit has a positive influence on acceptance of digital technologies.

Hypothesis 6 proposed a positive influence of habit on the acceptance of digital technologies within financial services organisations. However, the results revealed a non-significant relationship between habit and technology acceptance contradicting the initial expectation of this study. This result stands in contrast to prior studies that have often found a positive association between habit and technology acceptance (Venkatesh et al., 2012; Nikolopoulou et al., 2021). This discrepancy suggests that within the specific context of financial services organisations, the habitual nature of using digital technologies may not play as decisive a role in shaping acceptance as anticipated. The result suggests that organisations in the financial services sector should consider factors beyond habit when promoting the acceptance of digital technologies. Strategies that emphasise the tangible benefits of technology use and address specific challenges within the sector may be more effective in fostering acceptance, as opposed to relying solely on established habits.

5.8 Discussion pertaining to Hypothesis 7

Hypothesis 7 (H7): Acceptance of digital technologies positively influences employee mental health.

Hypothesis 7 proposed a positive relationship between the acceptance of digital technologies and employee mental health. The results validated this hypothesis, revealing a significant positive correlation between the two variables. This finding is in line with emerging literature that recognises the multifaceted impact of digital technologies, including digital health capabilities, on employee mental health (Sun et al., 2022; Schomakers et al., 2022; Brassey et al., 2021).

Sun et al. (2022) found that the use of digital technologies, particularly those focused on mental health, is linked to improved psychological wellbeing and performance, contributing positively to employees' mental health at work. While acknowledging the undeniable importance of technology for improving workflows and efficiency, the study also acknowledges the growing concern about its impact on employee mental health. Schomakers et al. (2022) stressed the dual role of technology in both contributing to and alleviating stress and poor mental health in the workplace is highlighted, emphasising the need for a nuanced understanding of its effects.

Therefore, the result aligns with existing research recognising digital tools as valuable resources for supporting employees' mental health and resilience. Utilising technology to enhance job performance is identified as a potential stress-reducer, especially when the technology is user-friendly, reducing cognitive load (Brassey et al., 2021). The positive role of social support in mitigating feelings of isolation is emphasised, highlighting the importance of a supportive work environment, training, and resources to help employees effectively navigate technological changes and minimise anxiety.

However, it is vital to acknowledge that, notwithstanding the evident benefits, evidence suggests that the acceptance of digital technologies in the workplace introduces a nuanced dynamic concerning employee mental health (Christensen et al., 2020). The improper use or excessive reliance on digital tools can potentially engender adverse effects on mental wellbeing. Issues such as prolonged screen time, the blurring of boundaries between professional and personal life, and the perpetual expectation of connectivity can collectively contribute to heightened stress, burnout, and various other mental health challenges for employees (Christensen et al., 2020). This highlights the need for organisations to strike a delicate balance in promoting technology adoption while concurrently fostering a supportive work environment that mitigates the potential negative impacts on the mental health of their workforce.

The development of positive habits in technology use is suggested as an effective strategy for lowering cognitive load and minimising stress. Moreover, perceiving the benefits of technology use as outweighing costs diminishes concerns about job insecurity and financial pressures, ultimately promoting better mental wellbeing among employees.

5.9 Discussion pertaining to Hypothesis 8

Hypothesis 8 (H8): Acceptance of digital technologies positively influences employee wellbeing.

Hypothesis 8 posited a positive influence of the acceptance of digital technologies on employee wellbeing, and the results supported this hypothesis. This aligns with prior studies which emphasised the importance of digital technologies in improving employee wellbeing in the workplace (Shamsi et al., 2021, Molino et al., 2020, and Khoza, 2022). When technology is user-friendly, it reduces cognitive load, increases efficiency, and minimises frustration or stress, contributing to overall wellbeing (Shamsi et al., 2021). The social platforms are crucial, as supportive interactions and positive feedback foster a sense of belonging, encouragement, and reduce feelings of isolation, positively influencing wellbeing (Khoza, 2022). The development of positive habits in technology use is another significant factor. This promotes efficiency, reduces cognitive load, and minimises stress associated with adapting to new routines, all of which positively contribute to employee wellbeing (Sun et al., 2022). When employees perceive the benefits of technology use as outweighing the costs, it diminishes concerns about job insecurity and economic pressures, adding another layer to the positive influence of technology acceptance on overall wellbeing in the workplace (Schomakers et al., 2022).

The result is interesting particularly especially considering the current era characterised by the Fourth Industrial Revolution (4IR), where digital technologies have assumed a central role in various aspects of life. The impact of COVID-19 further intensified the adoption of these technologies, necessitating flexible work routines and a shift towards remote work. This period also witnessed heightened social isolation, concurrently facilitated by digital technologies. Moreover, within the financial sector, a pivotal domain where innovation and technology are paramount, the implications become even more pronounced.

This confluence of factors suggests a critical need to carefully balance the adoption of digital technologies with the wellbeing of employees. The ongoing digital transformation, accentuated by the circumstances of the 4IR and the COVID-19 pandemic, underscores the intricate interplay between technological advancements and the mental wellbeing of the workforce. Trenerry et al. (2021) underscored this imperative, emphasising the growing importance for organisations to prioritise and closely monitor employee wellbeing as they undergo digital transformations. Thus, balancing the benefits of digital technology adoption with a proactive commitment to employee wellbeing emerges as a strategic imperative for sustainable and responsible organisational practices in the era of rapid technological evolution.

5.10 Conclusion

An extended application of the UTAUT was employed to investigate the relationship between technology acceptance and employee wellbeing, as well as mental health within financial services organisations. This chapter examined several hypotheses related to the impact of various factors on technology acceptance. Notably, the results revealed that performance expectancy, facilitating conditions, hedonic motivation and social influence significantly influenced the acceptance of digital technologies among users in financial services organisations. These findings are consistent with prior literature, supporting the UTAUT framework in this specific context. Moreover, the study found positive correlations between the acceptance of digital technologies and both employee mental health and employee wellbeing. The positive influence of technology acceptance on mental health and wellbeing was attributed to factors such as perceived benefits, user-friendly interfaces, social support, and positive emotional experiences. This research contributes to a holistic understanding of the interplay between technology acceptance and employee outcomes, emphasising the multifaceted impact of digital technologies on the wellbeing and mental health of employees in the financial services sector. Conclusions and recommendations are presented in the following chapter.

Differences from previously published research for employee mental health and wellbeing

The primary differentiation of this study lies in its extension of the UTAUT model to encompass employee wellbeing and mental health. This novel approach underscores the importance of considering the comprehensive effects of digital technology acceptance beyond productivity and efficiency metrics to include employees' wellbeing and mental health. It signals a paradigm shift towards a more holistic understanding of technology's impact in the workplace, aligning with recent scholarly efforts to understand the broader implications of digital technologies (Schomakers et al., 2022; Sun et al., 2022).

The extension of the UTAUT model to include employee wellbeing and mental health, as outlined in this study, reflects a significant advancement in technology acceptance research.

CHAPTER 6. CONCLUSIONS & RECOMMENDATIONS

6.1 Introduction

This chapter synthesises findings related to the impact of digital technologies on the mental health and wellbeing of employees in financial services in South Africa, addressing the research questions posed in Chapter 1. It integrates data analysis, literature review insights, and study results to offer comprehensive conclusions and actionable recommendations.

6.2 Conclusions regarding research question 1

"What factors influence the acceptance of digital technologies in financial services in South Africa?"

This study confirms the significance of performance expectancy, facilitating conditions, hedonic motivation, and social influence in influencing acceptance of digital technologies. Therefore, the study concludes that acceptance of digital technologies withing financial services organisations in South Africa is driven by the perceived performance of the technology, facilitating conditions, hedonic motivations, and social influence.

Performance expectancy (PE): Employees are likely to accept digital technologies when they believe these will enhance their job performance. This is consistent with the sector's emphasis on efficiency and productivity, where technology that improves performance is valued.

Facilitating conditions (FC): The presence of necessary support, infrastructure, and resources significantly influences technology acceptance. This includes adequate training, technical support, and a culture that encourages technology use, indicating the importance of organisational readiness in technology adoption.

Hedonic motivation (HM): The enjoyment and satisfaction derived from using digital technologies play a crucial role in their acceptance. Technologies that are engaging and enjoyable are more likely to be embraced by employees, underscoring the importance of user experience in technology design.

Social influence (SI): The perceptions and opinions of peers, superiors, and the broader organisational culture towards digital technologies significantly impact their acceptance. Positive social influence can encourage technology adoption, highlighting the role of social factors in shaping technology acceptance behaviours.

The study however found no significant influence of effort expectancy and habit on acceptance and suggests that while ease of use and habitual use are important, they are not the primary drivers of technology acceptance in this context. Instead, factors that directly relate to the perceived benefits of technology use, such as performance improvement, social support, enjoyment, and organisational facilitation, are more critical. This underscores the need for a holistic approach to technology implementation, one that goes beyond usability to include performance benefits, social dynamics, and organisational support systems.

6.3 Conclusions regarding research question 2

"What is the perceived influence of digital technologies on employee mental health in financial services in South Africa?

This study establishes that acceptance of digital technologies positively influences employee mental health. It is therefore concluded that if employees utilise digital technologies in the workplace, the result is an improvement in their mental health, holding all other factors constant.

While the study supports the hypothesis that the acceptance of digital technologies positively influences mental health, it is also important to acknowledge the importance of organisational context, technology implementation, and individual support to mitigate potential negative effects such as technostress and work-life balance disruption.

Digital technologies can enhance mental health by improving work efficiency, enabling flexible work arrangements, and fostering a sense of accomplishment and engagement. However, they can also contribute to stress, anxiety, and burnout due to increased workloads, constant connectivity expectations, and the pressure to adapt to new systems. Mitigating these negative impacts requires careful technology implementation, supportive organisational policies, and proactive measures to support employee mental health, emphasising the need for a balanced approach that considers both the advantages and potential drawbacks of digital technologies in the workplace.

6.4 Conclusions regarding research question 3

What is the perceived influence of Digital Technologies on employee wellbeing in financial services in South Africa?

This study concludes that the acceptance of digital technologies positively influences employee wellbeing. Thus, as more digital technologies are used, the result is an improvement in overall employee wellbeing, holding all other factors constant.

However, it is important to approach the result with caution because of the potential adverse effects of digital technologies. While digital technologies can lead to enhanced mental health, work engagement, and supportive work environments, contributing positively to overall employee wellbeing, it also carries the risk of adverse effects. These include increased work intensity, difficulty in disconnecting from work leading to blurred work-life boundaries, and potential stress from constant technology adaptation. To maximise the benefits and minimise the downsides, organisations must implement digital technologies thoughtfully. This entails developing comprehensive support systems, offering targeted training, and actively considering employee feedback to ensure technology use aligns with enhancing employee wellbeing rather than detracting from it.

6.5 Recommendations

Based on the findings that the acceptance of digital technologies significantly improves employee mental health and wellbeing, the following recommendations are provided to financial services organisations to enhance the acceptance of digital technologies in the workplace:

- Clear communication about the effectiveness and benefits of digital technologies in enhancing job performance is recommended to be provided to employees, with performance expectancy shown to impact their acceptance significantly.
- Despite no significant influence of effort expectancy being found, addressing potential sector-specific barriers, and simplifying technology interfaces, coupled with comprehensive training, are advised to foster technology adoption effectively.
- Leveraging social influence by utilising the persuasive power of peers and leadership is suggested to encourage broader acceptance. Additionally, ensuring the provision of necessary support systems, resources, and infrastructure to facilitate seamless digital technology adoption is emphasised as crucial.
- Introducing functional and enjoyable technologies, incorporating gamification and user-friendly design elements, is strongly recommended to increase their appeal and acceptance. Furthermore, integrating digital technologies into daily work routines to promote habitual use is suggested, reinforcing their use as part of the organisational culture.
- Frameworks for creating mentally healthy workplaces, the scrutiny of flexible work practices and their potential pitfalls, and the assessment of digital maturity are recommended for implementation. These offer strategic insights for fostering environments that support mental health amid digital transformation in today's digital work environment, where challenges such as technostress and work-life balance issues are prevalent.

- Financial services organisations are advised to foster a supportive environment by creating an organisational culture that acknowledges the psychological impacts of technology use and provides resources to help employees manage these impacts effectively. By implementing the suggested frameworks, financial services organisations are envisaged to foster an environment that supports the acceptance and effective utilisation of digital technologies and enhances employee mental health and wellbeing, reflecting a thoughtful approach to navigating the complexities of digital transformation.
- In light of the competitive pressures from Insuretech and Fintech entrants, it ought to be recognised that employees should be equipped with skills of a world-class calibre. A competency assessment, incorporating leadership skills, is recommended to be designed. It is proposed that employees be enabled to acquire the necessary skills to surpass expectations and to promote an environment of continuous learning. By developing skills, the method of pursuing business is recommended to be redefined, placing a higher value on people over processes and technology due to its necessity.

6.6 Possible limitations and challenges of the study

Limited to a specific population, the study focused on employees within financial services organisations exposed to digital technologies. It is acknowledged that the findings and conclusions derived from this study may not be directly applicable across other regions or industries. Hence, the generalisability of the results should be approached with caution. Due to the specificity of the sample of individuals, it is recognised that the sample may need to fully encapsulate the diversity and range of experiences present within the target population. Variations in factors within the population, such as socioeconomic status, education level, and cultural background, may need to be adequately captured by the study's findings.

The influence of external factors, which are beyond the control of the researchers, on the study's findings is acknowledged. Such factors, including but not limited to organisational changes and technological advancements, could affect the participants' perceptions and experiences of digital transformation, thereby impacting the study's outcomes.

The research addressed several gaps identified in the literature review, particularly emphasising the need for more context-specific analyses on the impact of digital technologies on employee wellbeing.

6.7 Suggestions for further research

Future research should aim to deepen the understanding of digital technology's impact on employee wellbeing and mental health by exploring several key areas:

- A focus on the long-term effects of digital technology acceptance, considering the complexity of technologies and individual differences in technology acceptance, is crucial. This approach facilitates a more nuanced comprehension of how digital technologies can enhance employee wellbeing in the workplace, urging organisations to adopt employee-centric technology strategies.
- To broaden the scope and enhance the generalisability of findings, future studies are advised to encompass a broader and more diverse population beyond the financial services sector, examining impacts across various industries and regions. Addressing the representation of diverse experiences, subsequent research should include participants from varied socioeconomic statuses, education levels, and cultural backgrounds to better understand how these factors' influence the relationship between digital technology use and mental health and wellbeing.
- The exploration of external factors such as organisational changes, technological advancements, and other elements that affect employees' perceptions and experiences of digital transformation is recommended. Longitudinal studies could offer valuable insights into these dynamics over time.
- Further investigation into the interplay between technology acceptance and mental health is suggested, including identifying additional mediating

factors like personal resilience or workplace policies that influence mental health outcomes. The role of organisational support mechanisms in mitigating the potential negative impacts of digital technology use warrants examination, focusing on the types of support that effectively foster a positive technological experience for employees.

- The emphasis on developing positive technology use habits and the perception that the benefits outweigh its costs highlights the need for research into interventions or programs that promote healthy digital habits among employees. Such studies could offer actionable strategies for organisations aiming to enhance mental wellbeing through technology.

REFERENCES

Abu Gharrah, A. S., & Aljaafreh, A. (2021). Why students use social networks for education: Extension of UTAUT2. Journal of Technology and Science Education, 11(1), 53-66. https://doi.org/10.3926/jotse.1081

Abu-Raddad, L. J., Chemaitelly, H., Ayoub, H. H., AlMukdad, S., Yassine, H. M., Al-Khatib, H. A., Smatti, M. K., Tang, P., Hasan, M. R., Coyle, P., Al-Kanaani, Z., Al-Kuwari, E., Jeremijenko, A., Kaleeckal, A. H., Latif, A. N., Shaik, R. M., Abdul-Rahim, H. F., Nasrallah, G. K., Al-Kuwari, M. G., Butt, A. A., et al (2022). Effect of mRNA vaccine boosters against SARS-CoV-2 Omicron infection in Qatar. The New England Journal of Medicine, 386, 1804-1816. https://doi.org/10.1056/NEJMoa2200797

Acemoglu, D., & Autor, D. (2011). Chapter 12 - Skills, Tasks and Technologies: Implications for Employment and Earnings. Handbook of Labor Economics, Volume 4, Part B, 1043-1171.

Acemoglu, D., & Autor, D. H. (2010, June). Skills, tasks and technologies: Implications for employment and earnings (NBER Working Paper No. w16082). SSRN. https://ssrn.com/abstract=1624142

Adner, R., Puranam, P., & Zhu, F. (2019). What is different about digital strategy? From quantitative to qualitative change. Strategy Science, 4(4), 253–261. http://pubsonline.informs.org/journal/stsc

Ajigini, O. A., & Chinamasa, T. J. W. (2023). Modelling Digital Transformation Within the Financial Sector. Information Resources Management Journal. https://doi.org/10.4018/irmj.320642

Alshammari, S. (2021). Determining the Factors that Affect the Use of Virtual Classrooms: A Modification of the UTAUT Model. Journal of Information Technology Education, 20, 117-135. https://www.informingscience.org/Publications/4709

Armstrong, B., & Lee, G. (2021). Digital business (2nd ed.). Silk Route Press.

Atluri, N., Cordina, J., Mango, P., & Velamoor, S. (2016, November 23). How tech-enabled consumers are reordering the healthcare landscape. McKinsey & Company. https://www.mckinsey.com/industries/healthcare/our-insights/how-tech-enabled-consumers-are-reordering-the-healthcare-landscape

Barley, S. R., Meyerson, D. E., & Grodal, S. (2010). E-mail as a source and symbol of stress. Organization Science, 22(4). https://doi.org/10.1287/orsc.1100.0573

Batucan, G. B., Gonzales, G. G., Balbuena, M. G., Pasaol, K. R. B., Seno, D. N., & Gonzales, R. R. (2022). An extended UTAUT model to explain factors affecting online learning system amidst COVID-19 pandemic: The case of a developing economy. Frontiers in Artificial Intelligence, 5, Article 768831. https://doi.org/10.3389/frai.2022.768831

Brougham, D., & Haar, J. (2017). Smart technology, artificial intelligence, robotics, and algorithms (STARA): Employees' perceptions of our future workplace. Journal of Management & Organization, https://doi.org/10.1017/jmo.2016.55Bryman, A., & Cramer, D. (2011). Quantitative data analysis with IBM SPSS 17, 18 & 19: A guide for social scientists (1st ed.). Routledge. https://doi.org/10.4324/9780203180990

Cai, J. (2022). Effectiveness of Employee Assistance Program Interventions for Mental Health. *Journal of Humanities, Arts and Social Science*, 6(3), 462-466. https://doi.org/10.26855/jhass.2022.09.027.

Carnevale, J. B., & Hatak, I. (2020). Employee adjustment and well-being in the era of COVID-19: Implications for human resource management. Journal of Business Research, 116, 183-187. https://doi.org/10.1016/j.jbusres.2020.05.037

Casey, T., & Wilson-Evered, E. (2012). Predicting uptake of technology innovations in online family dispute resolution services: An application and extension of the UTAUT. Computers in Human Behavior, 28(6), 2034-2045. https://doi.org/10.1016/j.chb.2012.05.022

Cetindamar Kozanoglu, D., & Abedin, B. (2021). Understanding the role of employees in digital transformation: Conceptualization of digital literacy of employees as a multi-dimensional organizational affordance. Journal of Enterprise Information Management, 34(6), 1649-1672. https://doi.org/10.1108/JEIM-01-2020-0010

Chao, C-M. (2019). Factors determining the behavioral intention to use mobile learning: An application and extension of the UTAUT model. Frontiers in Psychology, 10, 1652. https://doi.org/10.3389/fpsyg.2019.01652

Chatterjee, S., Rana, N. P., Tamilmani, K., & Sharma, A. (2021). The effect of AI-based CRM on organization performance and competitive advantage: An empirical analysis in the B2B context. Industrial Marketing Management, 97, 205-219. https://doi.org/10.1016/j.indmarman.2021.07.013

Christensen, T., Lægreid, P., & Røvik, K. A. (2020). Organization theory and the public sector: Instrument, culture and myth. Routledge.

Como, R., Hambley, L., & Domene, J. (2021). An exploration of work-life wellness and remote work during and beyond COVID-19. *Canadian Journal of Career Development*, *20*(1), 46-56. https://cjcd-rcdc.ceric.ca/index.php/cjcd/article/view/92

Cooper, R., & Baird, M. (2015). Bringing the "right to request" flexible working arrangements to life: From policies to practices. *Employee Relations*, *37*(5), 568-581. https://doi.org/10.1108/ER-07-2014-0085

Corrigan, J. (2022, February 28). Half of employees quit their job for their mental health in 2021. HRD. https://www.hcamag.com/us/specialization/benefits/half-of-employees-quit-their-job-for-their-mental-health-in-2021/326840

Davenport, T. H., & Westerman, G. (2018). Why so many high-profile digital transformations fail. Harvard Business Review, 9(4), 15. https://www.nutanix.com/content/dam/nutanix-cxo/pdf/Why%20So%20Many%20High-Profile%20Digital%20Transformations%20Fail.pdf

Dennis, D. (2021). Mental health issues affecting doctors working in intensive care units. Raine Medical Research Foundation. https://www.rainefoundation.org.au/research-stories/mental-health-issues-affecting-doctors-working-in-intensive-care-units/

Diener, E., Wirtz, D., Tov, W., et al. (2010). New well-being measures: Short scales to assess flourishing and positive and negative feelings. Social Indicators Research, 97, 143–156. https://doi.org/10.1007/s11205-009-9493-y

Dittes, S., Richter, S., Richter, A., & Smolnik, S. (2019). Toward the workplace of the future: How organizations can facilitate digital work. Business Horizons, 62(5), 649-661. https://doi.org/10.1016/j.bushor.2019.05.004

Donati, S., Viola, G., Toscano, F., & Zappalà, S. (2021). Not all remote workers are similar: Technology acceptance, remote work beliefs, and wellbeing of remote workers during the second wave of the COVID-19 pandemic. International Journal of Environmental Research and Public Health, 18(22), 12095. https://doi.org/10.3390/ijerph182212095

Dutz, A., & Löck, S. (2019). Competing risks in survival data analysis. Radiotherapy and Oncology, 130, 185-189. https://doi.org/10.1016/j.radonc.2018.09.007

Fedorko, I., Bačik, R., & Gavurova, B. (2021). Effort expectancy and social influence factors as main determinants of performance expectancy using electronic banking. Banks and Bank Systems, 16(2), 27-37. doi:10.21511/bbs.16(2).2021.03

Fernandez-Vidal, J., Perotti, F. A., Gonzalez, R., & Gasco, J. (2022). Managing digital transformation: The view from the top. *Journal of Business Research*, *152*, 29-41. https://doi.org/10.1016/j.jbusres.2022.07.020

Ferrell, O. C., Hartline, M., & Hochstein, B. W. (2021). Marketing strategy. Cengage Learning.

Field, A. (2018). *Discovering statistics using IBM SPSS statistics*. 5th ed. Sage Publications.

Furr, N., Ozcan, P., & Eisenhardt, K. M. (2022). What is digital transformation? Core tensions facing established companies on the global stage. Global Strategy Journal, 12(4), 595–618. https://doi.org/10.1002/gsj.1442

Galanti, T., De Vincenzi, C., Buonomo, I., & Benevene, P. (2023). Digital transformation: Inevitable change or sizable opportunity? The strategic role of HR management in Industry 4.0. Administrative Sciences, 13(2), Article 30. https://doi.org/10.3390/admsci13020030

George, D., & Mallery, P. (2019). IBM SPSS statistics 26 step by step: A simple guide and reference. Routledge.

Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2018). On the Fintech Revolution: Interpreting the Forces of Innovation, Disruption, and Transformation in Financial Services. Journal of Management Information Systems, 35(1), 220-265. https://doi.org/10.1080/07421222.2018.1440766

Groen, B. A., Van Triest, S. P., Coers, M., & Wtenweerde, N. (2018). Managing flexible work arrangements: Teleworking and output controls. *European Management Journal*, *36*(6), 727-735. https://doi.org/10.1016/j.emj.2018.01.007

Groth, M., Wu, Y., Nguyen, H., & Johnson, A. (2019). The Moment of Truth: A Review, Synthesis, and Research Agenda for the Customer Service Experience. Annual Review of Organizational Psychology and Organizational, 6, 89-113. https://www.annualreviews.org/doi/10.1146/annurev-orgpsych-012218-015056

Gurbaxani, V., & Dunkle, D. (2019). Gearing up for successful digital transformation. MIS Q. Executive, 18(3), 6.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. European business review, 31(1), 2-24.

Handzlik, M. K., Gengatharan, J. M., Frizzi, K. E., et al. (2023). Insulin-regulated serine and lipid metabolism drive peripheral neuropathy. Nature, 614, 118–124. https://doi.org/10.1038/s41586-022-05637-6

Hartelina, H., Lumban Batu, R., & Hidayanti, A. (2021). What can hedonic motivation do on decisions to use online learning services? International Journal of Data and Network Science, 5(2), 121-126. https://doi.org/10.5267/j.ijdns.2021.2.002

Harvey, S. B., Deady, M., Wang, M.-J., Mykletun, A., Butterworth, P., Christensen, H., & Mitchell, P. B. (2017). Is the prevalence of mental illness increasing in Australia? Evidence from national health surveys and administrative data, 2001–2014. The Medical Journal of Australia, 206(11), 490-493. https://www.mja.com.au/journal/2017/206/11/prevalence-mental-illness-increasing-australia-evidence-national-health-surveys

Hassan, J., Shehzad, D., Habib, U., Aftab, M. U., Ahmad, M., Kuleev, R., & Mazzara, M. (2022). The rise of cloud computing: data protection, privacy, and open research challenges—a systematic literature review (SLR). Computational intelligence and neuroscience, 1-14. https://doi.org/10.1016/j.joitmc.2023.100010

Hassan, M. S., Islam, M. A., Yusof, M. F., & Nasir, H. (2023). Users' fintech services acceptance: A cross-sectional study on Malaysian Insurance & takaful industry. Heliyon, 9(11), 1-15. doi: 10.1016/j.heliyon. 2023.e21130

Huang, C.-Y., & Kao, Y.-S. (2015). UTAUT2 based predictions of factors influencing the technology acceptance of phablets by DNP. Mathematical Problems in Engineering, 2015, Article ID 603747, 23 pages. https://doi.org/10.1155/2015/603747

Johnson, A., Dey, S., Nguyen, H., Groth, M., Joyce, S., Tan, L., Glozier, N., & Harvey, S. B. (2020). A review and agenda for examining how technology-driven changes at work will impact workplace mental health and employee wellbeing. Australian Journal of Management, 45(3), 402-424. https://journals.sagepub.com/doi/full/10.1177/0312896220922292

Khoza, N. G. (2022). A review of literature on the effective pedagogy strategies for online teaching and learning in higher education institutions: Lessons from the COVID-19 pandemic. European Journal of Education, 5(1), 43. https://doi.org/10.26417/738tqq65

Kılıç, S. (2016). Cronbach's alpha reliability coefficient -. *Journal of Mood Disorders, 6*, 47. https://doi.org/10.5455/JMOOD.20160307122823

Kozinets, R. V. (2021). Reprint: YouTube utopianism: Social media profanation and the clicktivism of capitalist critique. Journal of Business Research, 131, 349–365.

Kulviwat, S., Bruner, G. C., & Al-Shuridah, O. (2009). The role of social influence on adoption of high tech innovations: The moderating effect of public/private consumption. Journal of Business Research, 62(7), 706-712. https://doi.org/10.1016/j.jbusres.2007.04.014

Kumar, R. (2014). Research Methodology: a step-by-step guide for beginners (4th ed.).

Kurniasari, F., Utomo, P., & Jimmy, S. Y. (2023). Determinant factors of fintech adoption in organization using UTAUT theory approach. Journal of Business and Management Review, 4(2), 92-103.

Lebeau, E. (2022). Mental Health in a Digitalized Workplace. https://www.news-medical.net/health/Mental-Health-in-a-Digitalized-Workplace.aspx

Levitt, H. M., Bamberg, M., Creswell, J. W., Frost, D. M., Josselson, R., & Suárez-Orozco, C. (2018). Journal article reporting standards for qualitative primary, qualitative meta-analytic, and mixed methods research in psychology: The APA Publications and Communications Board Task Force Report. American Psychologist, 73(1), 26–46. http://dx.doi.org/10.1037/amp0000151

Limayem, M., Hirt, S. G., & Cheung, C. M. K. (2007). How Habit Limits the Predictive Power of Intention: The Case of Information Systems Continuance. MIS Quarterly, 31(4), 705–737. https://doi.org/10.2307/25148817

Lock Associates Group. (2024, February 24). *Safeguarding the mental health of employees in the financial services sector*. Loch Associates. https://lochassociates.co.uk/safeguarding-the-mental-health-of-employees-in-the-financial-services-sector/

Mangubat, J., & Batucan, G. (2023). Teacher's intentions to use GeoGebra in teaching mathematics: An empirical study to validate technology acceptance model in the Philippines. Magister - Journal of Educational Research, 2(2), 42–66. Retrieved from http://errc.ctu.edu.ph/ojs/index.php/magister/article/view/39

Matema, T., & Kariuki, P. (2022). The impact of social media on social cohesion in South Africa. Journal of Economics and Behavioral Studies, 14(2 (J)), 1-12. http://dx.doi.org/10.22610/jebs.v14i2(J).3249.

McClure, P. K. (2017). "You're Fired," Says the Robot: The Rise of Automation in the Workplace, Technophobes, and Fears of Unemployment. Social Science Computer Review, 36(2), 139-156.

Molino M, Ingusci E, Signore F, Manuti A, Giancaspro ML, Russo V, Zito M, Cortese CG. Wellbeing Costs of Technology Use during Covid-19 Remote Working: An Investigation Using the Italian Translation of the Technostress Creators Scale. Sustainability. 2020; 12(15):5911. https://doi.org/10.3390/su12155911

Moorthy, K., Tzu Yee, T., Chun T'ing, L., & Vija Kumaran, V. (2019). Habit and hedonic motivation are the strongest influences in mobile learning behaviours among higher education students in Malaysia. Australasian Journal of Educational Technology, 35(4). https://doi.org/10.14742/ajet.4432

Myovella, G., Karacuka, M., & Haucap, J. (2020). Digitalization and economic growth: A comparative analysis of Sub-Saharan Africa and OECD economies. *Telecommunications Policy*, *44*(2), 101856. https://doi.org/10.1016/j.telpol.2019.101856

Neuman, D. (2014). Qualitative research in educational communications and technology: A brief introduction to principles and procedures. Journal of Computing in Higher Education, 26, 69–86. https://doi.org/10.1007/s12528-014-9078-x

Nikolopoulou, K., Gialamas, V. & Lavidas, K. Acceptance of mobile phone by university students for their studies: an investigation applying UTAUT2 model. Educ Inf Technol 25, 4139–4155 (2020). https://doi.org/10.1007/s10639-020-10157-9

Nikolopoulou, K., Gialamas, V., & Lavidas, K. (2021). Habit, hedonic motivation, performance expectancy and technological pedagogical knowledge affect teachers' intention to use mobile internet. Computers and Education Open, 2, Article 100041. https://doi.org/10.1016/j.caeo.2021.100041

Page, K. M., & Vella-Brodrick, D. A. (2009). The 'what','why'and 'how'of employee well-being: A new model. *Social indicators research*, *90*, 441-458. https://doi.org/10.1007/s11205-008-9270-3

Peñarroja, V., Sánchez, J., Gamero, N., Orengo, V., & Zornoza, A. M. (2019). The influence of organisational facilitating conditions and technology acceptance factors on the effectiveness of virtual communities of practice. Behaviour & Information Technology, 38(8), 845-857. https://doi.org/10.1080/0144929X.2018.1564070

Perlow, L. A. (2012). Sleeping with your smartphone: How to break the 24/7 habit and change the way you work. Harvard Business Press.

Petrie, K., Milligan-Saville, J., Gayed, A., Deady, M., Phelps, A., Dell, L., & Harvey, S. B. (2018). Prevalence of PTSD and common mental disorders amongst ambulance personnel: a systematic review and meta-analysis. *Social psychiatry and psychiatric epidemiology*, *53*, 897-909. https://doi.org/10.1007/s00127-018-1539-5

Planas, D., Bruel, T., Grzelak, L., et al. (2021). Sensitivity of infectious SARS-CoV-2 B.1.1.7 and B.1.351 variants to neutralizing antibodies. Nature Medicine, 27, 917–924. https://doi.org/10.1038/s41591-021-01318-5

Ramírez-Correa PE, Arenas-Gaitán J, Rondán-Cataluña FJ, Grandon EE, Ramírez-Santana M (2023) Adoption of social networking sites among older adults: The role of the technology readiness and the generation to identifying segments. PLoS ONE 18(4): e0284585. https://doi.org/10.1371/journal.pone.0284585

Ramsden-Knowles, B., & Stainback, D. (2023). The Resilience Revolution: PwC's Global Crisis and Resilience Survey 2023. https://www.pwc.com/gx/en/crisis/pwc-global-crisis-resilience-survey-2023.pdf

Rasoolimanesh, S. M. (2022). Discriminant validity assessment in PLS-SEM: A comprehensive composite-based approach. ResearchGate. https://www.researchgate.net/publication/356961783_Discriminant_validity_assessment_in_PLS-SEM_A_comprehensive_composite-based_approach

Richter, A., Heinrich, P., Stocker, A., & Schwabe, G. (2018). The Interplay of Human and Computer in Future Work Practices as an Interdisciplinary (Grand) Challenge. Digital Work Design, 60(3), 259-264. https://link.springer.com/article/10.1007/s12599-018-0534-4

Saunders, M., Lewis, P., & Thornhill, A. (2009). *Research methods for business students*. Pearson education.

Schomakers, E., Lidynia, C., Vervier, L. S., Calero Valdez, A., & Ziefle, M. (2022). Applying an extended UTAUT2 model to explain user acceptance of lifestyle and therapy mobile health apps: Survey study. JMIR mHealth and uHealth, 10(1), e27095. https://doi.org/10.2196/27095

Selimović, J., Pilav-Velić, A., & Krndžija, L. (2021). Digital workplace transformation in the financial service sector: Investigating the relationship between employees' expectations and intentions. Technology in Society, 66, 101640. https://doi.org/10.1016/j.techsoc.2021.101640Jefferson, T.,

Shaikh, A., Peprah, E., Mohamed, R. H., et al. (2021). COVID-19 and mental health: A multi-country study—the effects of lockdown on the mental health of young adults. Middle East Current Psychiatry, 28(51). https://doi.org/10.1186/s43045-021-00116-6

Silver, L., & Johnson, C. (2020). Sub-saharan Africans say internet use has positively impacted education, personal relationships and economy. Pew Research Center's Global Attitudes Project. https://www.pewresearch.org/global/2018/10/09/sub-saharan-africans-say-internet-use-has-positively-impacted-education-personal-relationships-and-economy/

Singh, P., Bala, H., Lal Dey, B., & Filieri, R. (2022). Enforced remote working: The impact of digital platform-induced stress and remote working experience on technology exhaustion and subjective wellbeing. Journal of Business Research, 151, 269-286. https://www.sciencedirect.com/science/article/pii/S0148296322006099?via%3Dihub

Singh, S., Roy, D., Sinha, K., Parveen, S., Sharma, G., & Joshi, G. (2020). Impact of COVID-19 and lockdown on mental health of children and adolescents: A narrative review with recommendations. Psychiatry Research, 293, 113429. https://doi.org/10.1016/j.psychres.2020.113429

Spencer, E. A., Brassey, J., & Heneghan, C. (2021). Viral cultures for coronavirus disease 2019 infectivity assessment: A systematic review. Clinical Infectious Diseases, 73(11), e3884–e3899. https://doi.org/10.1093/cid/ciaa1764

Sukendro, S., Habibi, A., Khaeruddin, K., Indrayana, B., Syahruddin, S., Makadada, F. A., & Hakim, H. (2020). Using an extended Technology Acceptance Model to understand students' use of e-learning during Covid-19: Indonesian sport science education context. Heliyon, 6(11), 1-10. https://doi.org/10.1016/j.heliyon.2020.e05410

Sun, J., Ivascu, L., Ivascu, L., Iqbal, K., & Mansoor, A. (2022). How Did Work-Related Depression, Anxiety, and Stress Hamper Healthcare Employee Performance during COVID-19? The Mediating Role of Job Burnout and Mental Health. International Journal of Environmental Research and Public Health, 19(16), 10359.

Sun, J., Shen, H., Ibn-ul-Hassan, S., Riaz, A., & Domil, A. E. (2022). The association between digitalization and mental health: The mediating role of wellbeing at work. Frontiers in Psychiatry, 13, 934357. doi: 10.3389/fpsyt.2022.934357

Taherdoost, H. (2018). A review of technology acceptance and adoption models and theories. Procedia manufacturing, 22, 960-967. https://doi.org/10.1016/j.promfg.2018.03.137

Tamilmani, K., Rana, N. P., Prakasam, N., & Dwivedi, Y. K. (2019). The battle of Brain vs. Heart: A literature review and meta-analysis of “hedonic motivation” use in UTAUT2. International Journal of Information Management, 46, 222-235. https://doi.org/10.1016/j.ijinfomgt.2019.01.008

Tarafdar, M., & Ragu-Nathan, B. S. (2005). Exploring the Impact of Technostress on Productivity. Proceedings of the 36th Annual Meeting of the Decision Science Institute, San Francisco.

Tavakol, M., & Dennick, R. (2011). Making sense of Cronbach's alpha. *International journal of medical education*, *2*, 53. https://doi.org/10.5116%2Fijme.4dfb.8dfd

Trenerry, B., Chng, S., Wang, Y., Suhaila, Z. S., Lim, S. S., Lu, H. Y., & Oh, P. H. (2021). Preparing workplaces for digital transformation: An integrative review and framework of multi-level factors. Frontiers in psychology, 822-832. https://doi.org/10.3389/fpsyg.2021.620766

Van der Lippe, T., & Lippényi, Z. (2020). Co-workers working from home and individual and team performance. *New technology, work and employment*, *35*(1), 60-79. https://doi.org/10.1111/ntwe.12153

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User Acceptance of Information Technology: Toward a Unified View. MIS Quarterly, 27(3), 425-478. https://doi.org/10.2307/30036540

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS quarterly*, 157-178. https://doi.org/10.2307/41410412

Warner, K. S., & Wäger, M. (2019). Building dynamic capabilities for digital transformation: An ongoing process of strategic renewal. *Long range planning*, *52*(3), 326-349. https://doi.org/10.1016/j.lrp.2018.12.001

Whiteford, H. A., Degenhardt, L., Rehm, J., Baxter, A. J., Ferrari, A. J., Erskine, H. E., et al. (2013). Global burden of disease attributable to mental and substance use disorders: findings from the Global Burden of Disease Study 2010. *The Lancet, 382(9904)*, 1575-1586. https://doi.org/10.1016/S0140-6736(13)61611-6

Wilson, W. J. (1996). When Work Disappears. Political Science Quarterly, 111(4), 567–595. https://doi.org/10.2307/2152085

World Health Organization. (2020). Mental health and psychosocial considerations during the COVID-19 outbreak, 18 March 2020 (No. WHO/2019-nCoV/MentalHealth/2020.1). World Health Organization.

Xie, J., Ye, L., Huang, W., & Ye, M. (2021). Understanding FinTech platform adoption: impacts of perceived value and perceived risk. Journal of Theoretical and Applied Electronic Commerce Research, 16(5), 1893-1911. https://doi.org/10.3390/jtaer16050106

Yohanes et al. (2020) Behavioral intention to adopt FinTech services: An extension of the unified theory of acceptance and use of technology - ScienceDirect

Zhang, C., Yu, M. C., & Marin, S. (2021). Exploring public sentiment on enforced remote work during COVID-19. Journal of Applied Psychology, 106(6), 797–810. https://psycnet.apa.org/fulltext/2021-56704-001.html

Zhou, R., Luo, Z., Zhong, S., Zhang, X., & Liu, Y. (2022). The impact of social media on employee mental health and behavior based on the context of intelligence-driven digital data. *International journal of environmental research and public health*, *19*(24), 16965. https://doi.org/10.3390%2Fijerph192416965

APPENDICES

APPENDIX A: PARTICIPANT INFORMATION SHEET AND QUESTIONNAIRE

Start of Block: Cover letter and respondent consent form

Dear Respondent,

My name is Eleanor Sansovini, and I am a master's student in Digital Business at the University of Witwatersrand, Johannesburg, under the supervision of Ayanda Magida.
I am researching the impact of digital technologies on employee mental health and wellbeing in the South African financial services sector (Digital technologies refer to those that have been implemented or adopted at work).
I invite you to participate in a 10-minute questionnaire. The survey does not require your name or any other personal details, and your participation is voluntary. All information you provide will be treated as confidential and stored securely. Your responses will only be accessible to the research team and will not be shared with third parties. You are under no obligation to answer any questions that you do not wish to respond to, and there are no direct benefits associated with participating in this research study.
To commence the survey, please choose "Yes, I consent", which indicates you have read and understood the above information. Conversely, if you opt not to participate in the survey, please select "No, I do not consent" and you will be exited from the survey.

Thank you,
Eleanor Sansovini

End of Block: Cover letter and respondent consent form

Start of Block: Consent Form

Consent Do you consent to participate?

○ Yes, I consent (1)

○ No, I do not consent (2)

Skip To: End of Survey If Do you consent to participate? != Yes, I consent

End of Block: Consent Form

Start of Block: Demographics

D Gender Please select your gender

○ Male (1)

○ Female (2)

○ Non-binary/third gender (3)

○ Prefer not to say (4)

D Age Please select your age range

- 18-25 (1)
- 26-35 (2)
- 36-49 (3)
- 50-65 (4)

D Education Please select your highest education level

- High School (1)
- Undergraduate Degree (2)
- Honours Degree (3)
- Masters Degree (4)
- Professional Degree (5)
- Other (Specify) (6) ____________________

D Ethnicity Please select your ethnicity

- ○ Black African (1)
- ○ White (2)
- ○ Mixed Race (3)
- ○ Indian/Asian (4)
- ○ Other (Specify) (5) ____

D Industry Please select which sector of the financial services industry you are currently working

- ○ Banking Services (1)
- ○ Investment and Wealth Management (2)
- ○ Insurance Services (3)
- ○ Financial Advisory and Consulting (5)
- ○ Other (Specify) (6) ____

D Title Please select your title

- Executive (1)
- Senior Management (2)
- Middle Management (3)
- Staff (4)
- Contractor (5)
- Other (Specify) (6) ____

D Geography Please select your geographical location

- Southern Africa (1)
- North Africa (2)
- West Africa (3)
- East Africa (4)
- Other (Specify) (6) ____

End of Block: Demographics

Start of Block: Performance

PE In the following statements, the aim is to explore your perspective on how digital technologies can improve job performance, and job satisfaction, and positively affect the mental health and wellbeing of employees.

End of Block: Performance

Start of Block: PE Performance Expectancy

PE1 I can improve my efficiency by effectively using digital technologies for work purposes.

- ○ Strongly Disagree (1)
- ○ Disagree (2)
- ○ Somewhat Disagree (3)
- ○ Neither Agree nor Disagree (4)
- ○ Somewhat Agree (5)
- ○ Agree (6)
- ○ Strongly Agree (7)

PE2 I can increase my productivity and information utilisation by effectively using digital technologies for work purposes.

- ◯ Strongly Disagree (1)
- ◯ Disagree (2)
- ◯ Somewhat Disagree (3)
- ◯ Neither Agree nor Disagree (4)
- ◯ Somewhat Agree (5)
- ◯ Agree (6)
- ◯ Strongly Agree (7)

End of Block: PE Performance Expectancy

Start of Block: EE Effort Expectancy

EE In the following statements, the aim is to examine the user-friendliness of digital technologies on employees' wellbeing and mental health.

End of Block: EE Effort Expectancy

Start of Block: EE Effort Expectancy

EE1 I find it easy to use digital technologies for work purposes.

- Strongly Disagree (1)
- Disagree (7)
- Somewhat Disagree (2)
- Neither Agree nor Disagree (3)
- Somewhat Agree (4)
- Agree (6)
- Strongly Agree (5)

EE2 It is easy for me to use digital technologies for work and productivity.

- Strongly Disagree (1)
- Disagree (2)
- Somewhat Disagree (3)
- Neither Agree nor Disagree (4)
- Somewhat Agree (5)
- Agree (6)
- Strongly Agree (7)

End of Block: EE Effort Expectancy

Start of Block: SI Social Influence

SI In the following statements, the aim is to explore the perspectives on the utilisation of digital technologies.

End of Block: SI Social Influence

Start of Block: SI Social Influence

SI1 The people around me attach great importance to using digital technologies for work purposes.

○ Strongly Disagree (1)

○ Disagree (7)

○ Somewhat Disagree (2)

○ Neither Agree nor Disagree (3)

○ Somewhat Agree (4)

○ Agree (6)

○ Strongly Agree (5)

SI2 My work environment encourages me to use digital technologies effectively.

- Strongly Disagree (1)
- Disagree (2)
- Somewhat Disagree (3)
- Neither Agree nor Disagree (4)
- Somewhat Agree (5)
- Agree (6)
- Strongly Agree (7)

End of Block: SI Social Influence

Start of Block: FC Facilitating Condition

FC In the following statements, the aim is to explore respondents' perception of the technical infrastructure that supports the use of digital technologies.

End of Block: FC Facilitating Condition

Start of Block: FC Facilitating Condition

FC1 It is easy for me to make use of digital technologies for work if there are resources available.

- Strongly Disagree (1)
- Disagree (2)
- Somewhat Disagree (3)
- Neither Agree nor Disagree (4)
- Somewhat Agree (5)
- Agree (6)
- Strongly Agree (7)

FC2 I can get help in solving problems by using digital technologies for work purposes.

- Strongly Disagree (1)
- Disagree (2)
- Somewhat Disagree (3)
- Neither Agree nor Disagree (4)
- Somewhat Agree (5)
- Agree (6)
- Strongly Agree (7)

End of Block: FC Facilitating Condition

Start of Block: TA Technology Adoption

TA. The following statements aim to explore whether employees within organisations demonstrate intention to use a new technology.

End of Block: TA Technology Adoption

Start of Block: TA Technology Adoption

TA1. I intend to continue using digital technologies for work purposes.

- Strongly Disagree (1)
- Disagree (2)
- Somewhat Disagree (3)
- Neither Agree nor Disagree (4)
- Somewhat Agree (5)
- Agree (6)
- Strongly Agree (7)

TA2. I intend to recommend the utilisation of digital technologies for enhancing workplace efficiency to others.

- ○ Strongly Disagree (1)
- ○ Disagree (2)
- ○ Somewhat Disagree (3)
- ○ Neither Agree nor Disagree (4)
- ○ Somewhat Agree (5)
- ○ Agree (6)
- ○ Strongly Agree (7)

End of Block: TA Technology Adoption

Start of Block: TA Technology Adoption

TA3. I can use digital technologies effectively for work purposes.

- Strongly Disagree (1)
- Disagree (2)
- Somewhat Disagree (3)
- Neither Agree nor Disagree (4)
- Somewhat Agree (5)
- Agree (6)
- Strongly Agree (7)

TA4. I can recommend that digital technologies enable data collection, accessibility and analytics to others for work purposes.

- Strongly Disagree (1)
- Disagree (2)
- Somewhat Disagree (3)
- Neither Agree nor Disagree (4)
- Somewhat Agree (5)
- Agree (6)
- Strongly Agree (7)

End of Block: TA Technology Adoption

Start of Block: HM Hedonic Motivation

HM In the following statements, the aim is to explore the enjoyment derived when using technological systems.

End of Block: HM Hedonic Motivation

Start of Block: HM Hedonic Motivation

HM1 Using digital technologies in my job enhances my ability to complete tasks expeditiously.

- Strongly Disagree (1)
- Disagree (2)
- Somewhat Disagree (3)
- Neither Agree nor Disagree (4)
- Somewhat Agree (5)
- Agree (6)
- Strongly Agree (7)

HM2 Using digital technologies in my job increases my productivity.

- ◯ Strongly Disagree (1)
- ◯ Disagree (2)
- ◯ Somewhat Disagree (3)
- ◯ Neither Agree nor Disagree (4)
- ◯ Somewhat Agree (5)
- ◯ Agree (6)
- ◯ Strongly Agree (7)

End of Block: HM Hedonic Motivation

Start of Block: H Habit

Habit The following statements assess the extent of behaviour in performance and its potential to enhance efficiency and reduce cognitive burden.

End of Block: H Habit

Start of Block: H Habit

H1 Using digital technologies for work purposes has become natural to me.

- Strongly Disagree (1)
- Disagree (2)
- Somewhat Disagree (3)
- Neither Agree nor Disagree (4)
- Somewhat Agree (5)
- Agree (6)
- Strongly Agree (7)

H2 The use of digital technologies at work has become a habit for me.

- Strongly Disagree (1)
- Disagree (2)
- Somewhat Disagree (3)
- Neither Agree nor Disagree (4)
- Somewhat Agree (5)
- Agree (6)
- Strongly Agree (7)

End of Block: H Habit

Start of Block: WB Wellbeing

WB In the following statements, the aim is to assess how technology is perceived and whether the utilisation of user-friendly technology bolsters employee wellbeing.

End of Block: WB Wellbeing

Start of Block: WB Wellbeing

WB1 My employer has programs and policies that allow me to be flexible in where, how much or when I work (for example, through telecommuting, part-time options or flexi-time) when using digital technologies.

- Strongly Disagree (1)
- Disagree (2)
- Somewhat Disagree (3)
- Neither Agree nor Disagree (4)
- Somewhat Agree (5)
- Agree (6)
- Strongly Agree (7)

WB2 I am satisfied with the employee recognition practices of my employer since digital technologies have been introduced in the workplace.

- ○ Strongly Disagree (1)
- ○ Disagree (2)
- ○ Somewhat Disagree (3)
- ○ Neither Agree nor Disagree (4)
- ○ Somewhat Agree (5)
- ○ Agree (6)
- ○ Strongly Agree (7)

WB3 I am satisfied with the work-life balance practices offered by my employer since the introduction of digital technologies.

- ◯ Strongly Disagree (1)
- ◯ Disagree (2)
- ◯ Somewhat Disagree (3)
- ◯ Neither Agree nor Disagree (4)
- ◯ Somewhat Agree (5)
- ◯ Agree (6)
- ◯ Strongly Agree (7)

End of Block: WB Wellbeing

Start of Block: MH Mental Health

MH The following statements aim to determine when employees leverage technology to improve their job performance and whether it can potentially reduce job-related mental health issues.

End of Block: MH Mental Health

Start of Block: MH Mental Health

MH1 My employer provides the resources necessary for me to meet my mental health needs when using digital technologies for work purposes.

- Strongly Disagree (1)
- Disagree (2)
- Somewhat Disagree (3)
- Neither Agree nor Disagree (4)
- Somewhat Agree (5)
- Agree (6)
- Strongly Agree (7)

MH2 My employer provides sufficient resources to help manage my stress related to using digital technologies for work purposes.

- Strongly Disagree (1)
- Disagree (2)
- Somewhat Disagree (3)
- Neither Agree nor Disagree (4)
- Somewhat Agree (5)
- Agree (6)
- Strongly Agree (7)

MH3 My employer provides a stress-free work environment using digital technologies for work purposes.

- Strongly Disagree (1)
- Disagree (2)
- Somewhat Disagree (3)
- Neither Agree nor Disagree (4)
- Somewhat Agree (5)
- Agree (6)
- Strongly Agree (7)

End of Block: MH Mental Health

APPENDIX B: ANALYSIS TABLES

CFA MODEL

Computation of degrees of freedom (Default model)

Number of distinct sample moments:	253
Number of distinct parameters to be estimated:	83
Degrees of freedom (253 - 83):	170

Result (Default model)

Minimum was achieved

Chi-square = 269,136

Degrees of freedom = 170

Probability level = ,000

Group number 1 (Group number 1 - Default model)

Estimates (Group number 1 - Default model)

Scalar Estimates (Group number 1 - Default model)

Maximum Likelihood Estimates

Regression Weights: (Group number 1 - Default model)

	Estimate	S.E.	C.R.	P	Label

PE1	<---	PE_	1				
PE2	<---	PE_	1,006	0,037	27,252	***	par_1
EE1	<---	EE_	1				
EE2	<---	EE_	1,357	0,12	11,291	***	par_2
FC1	<---	FC_	1				
FC2	<---	FC_	1,013	0,081	12,519	***	par_3
HM1	<---	HM_	1				
HM2	<---	HM_	0,915	0,048	19,126	***	par_4
H1	<---	HA_	1				
H2	<---	HA_	1,019	0,056	18,356	***	par_5
WB1	<---	WB_	1				
WB2	<---	WB_	0,976	0,103	9,493	***	par_6
WB3	<---	WB_	1,119	0,115	9,714	***	par_7
MH1	<---	MH_	1				
MH2	<---	MH_	0,885	0,051	17,227	***	par_8
MH3	<---	MH_	0,816	0,061	13,315	***	par_9
SI1	<---	SI_	1				
SI2	<---	SI_	1,99	0,372	5,343	***	par_10
TA4	<---	TA_	1				
TA3	<---	TA_	1,03	0,089	11,61	***	par_11
TA2	<---	TA_	1,026	0,091	11,314	***	par_12
TA1	<---	TA_	1,122	0,088	12,82	***	par_13

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
PE1	<---	PE_	0,954
PE2	<---	PE_	0,986
EE1	<---	EE_	0,73
EE2	<---	EE_	0,973
FC1	<---	FC_	0,867
FC2	<---	FC_	0,77
HM1	<---	HM_	0,937
HM2	<---	HM_	0,894
H1	<---	HA_	0,894

H2	<---	HA_	0,938
WB1	<---	WB_	0,694
WB2	<---	WB_	0,797
WB3	<---	WB_	0,818
MH1	<---	MH_	0,938
MH2	<---	MH_	0,881
MH3	<---	MH_	0,769
SI1	<---	SI_	0,416
SI2	<---	SI_	0,82
TA4	<---	TA_	0,753
TA3	<---	TA_	0,83
TA2	<---	TA_	0,811
TA1	<---	TA_	0,891

Covariances: (Group number 1 - Default model)

			Estimat e	S.E.	C.R.	P	Lab el
PE_	<-->	EE_	0,805	0,13 2	6,0 89	** *	par _14
PE_	<-->	FC_	0,829	0,13 1	6,3 21	** *	par _15
PE_	<-->	HM_	0,695	0,12 1	5,7 24	** *	par _16
PE_	<-->	HA_	0,622	0,12 4	5,0 03	** *	par _17
PE_	<-->	WB_	0,332	0,13 7	2,4 27	0,0 15	par _18
PE_	<-->	MH_	0,291	0,16	1,8 15	0,0 7	par _19
PE_	<-->	SI_	0,412	0,09 9	4,1 42	** *	par _20
PE_	<-->	TA_	0,714	0,11 6	6,1 66	** *	par _21
EE_	<-->	FC_	0,658	0,10 7	6,1 73	** *	par _22
EE_	<-->	HM_	0,502	0,09 2	5,4 42	** *	par _23
EE_	<-->	HA_	0,607	0,10 4	5,8 45	** *	par _24
EE_	<-->	WB_	0,352	0,1	3,5 09	** *	par _25
EE_	<-->	MH_	0,288	0,11	2,6 17	0,0 09	par _26
EE_	<-->	SI_	0,324	0,07 8	4,1 49	** *	par _27
EE_	<-->	TA_	0,467	0,08 6	5,4 43	** *	par _28
FC_	<-->	HM_	0,809	0,10 8	7,5 18	** *	par _29

FC_	<-->	HA_	0,793	0,112	7,061	***	par_30
FC_	<-->	WB_	0,463	0,116	3,982	***	par_31
FC_	<-->	MH_	0,463	0,131	3,529	***	par_32
FC_	<-->	SI_	0,46	0,1	4,624	***	par_33
FC_	<-->	TA_	0,755	0,105	7,202	***	par_34
HM_	<-->	HA_	0,852	0,112	7,587	***	par_35
HM_	<-->	WB_	0,431	0,111	3,877	***	par_36
HM_	<-->	MH_	0,321	0,124	2,587	0,01	par_37
HM_	<-->	SI_	0,345	0,08	4,302	***	par_38
HM_	<-->	TA_	0,762	0,103	7,41	***	par_39
HA_	<-->	WB_	0,565	0,123	4,593	***	par_40
HA_	<-->	MH_	0,391	0,131	2,982	0,003	par_41
HA_	<-->	SI_	0,388	0,089	4,372	***	par_42
HA_	<-->	TA_	0,723	0,104	6,932	***	par_43
WB_	<-->	MH_	1,406	0,214	6,584	***	par_44
WB_	<-->	SI_	0,368	0,094	3,9	***	par_45
WB_	<-->	TA_	0,418	0,101	4,136	***	par_46
MH_	<-->	SI_	0,391	0,102	3,842	***	par_47
MH_	<-->	TA_	0,309	0,106	2,906	0,004	par_48
SI_	<-->	TA_	0,337	0,077	4,357	***	par_49
e26	<-->	EE_	0,136	0,032	4,284	***	par_50
e17	<-->	e28	0,229	0,055	4,197	***	par_51
e19	<-->	e22	0,277	0,09	3,08	0,002	par_52

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P
Default model	83	269,136	170	0

Saturated model	253	0	0	
Independence model	22	3445,033	231	0

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	0,083	0,882	0,825	0,593
Saturated model	0	1		
Independence model	0,683	0,185	0,107	0,169

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2
Default model	0,922	0,894	0,97	0,958
Saturated model	1		1	
Independence model	0	0	0	0

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	0,736	0,678	0,713
Saturated model	0	0	0
Independence model	1	0	0

NCP

Model	NCP	LO 90	HI 90
Default model	99,136	58,415	147,786
Saturated model	0	0	0
Independence model	3214,033	3027,804	3407,586

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	1,556	0,573	0,338	0,854
Saturated model	0	0	0	0
Independence model	19,913	18,578	17,502	19,697

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	0,058	0,045	0,071	0,155
Independence model	0,284	0,275	0,292	0

AIC

Model	AIC	BCC	BIC	CAIC
Default model	435,136	460,589	697,337	780,337
Saturated model	506	583,587	1305,241	1558,241
Independence model	3489,033	3495,779	3558,532	3580,532

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	2,515	2,28	2,796	2,662
Saturated model	2,925	2,925	2,925	3,373
Independence model	20,168	19,091	21,287	20,207

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	130	139
Independence model	14	15

SEM RESULTS

Models

Default model (Default model)

Notes for Model (Default model)

Computation of degrees of freedom (Default model)

Number of distinct sample moments:	253
Number of distinct parameters to be estimated:	64
Degrees of freedom (253 - 64):	189

Result (Default model)

Minimum was achieved

Chi-square = 521,412

Degrees of freedom = 189

Probability level = ,000

Group number 1 (Group number 1 - Default model)

Estimates (Group number 1 - Default model)

Scalar Estimates (Group number 1 - Default model)

Maximum Likelihood Estimates

Regression Weights: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
TA_	<---	PE_	0,106	0,031	3,458	***	par_14
TA_	<---	EE_	-0,084	0,072	-1,167	0,243	par_15
TA_	<---	FC_	0,425	0,121	3,507	***	par_16
TA_	<---	HM_	0,294	0,111	2,647	0,008	par_17
TA_	<---	HA_	0,044	0,086	0,518	0,605	par_18
TA_	<---	SI_	0,249	0,094	2,653	0,008	par_19

MH_	<---	TA_	0,53	0,162	3,268	0,001	par_20
WB_	<---	TA_	0,679	0,155	4,39	***	par_21
PE1	<---	PE_	1				
PE2	<---	PE_	0,944	0,04	23,362	***	par_1
EE1	<---	EE_	1				
EE2	<---	EE_	1,402	0,166	8,426	***	par_2
FC1	<---	FC_	1				
FC2	<---	FC_	1,114	0,098	11,375	***	par_3
HM1	<---	HM_	1				
HM2	<---	HM_	0,917	0,048	19,034	***	par_4
H1	<---	HA_	1				
H2	<---	HA_	1,015	0,065	15,552	***	par_5
WB1	<---	WB_	1				
WB2	<---	WB_	1,004	0,107	9,343	***	par_6
WB3	<---	WB_	0,968	0,112	8,673	***	par_7
MH1	<---	MH_	1				
MH2	<---	MH_	0,892	0,053	16,846	***	par_8
MH3	<---	MH_	0,864	0,062	13,861	***	par_9
SI1	<---	SI_	1				
SI2	<---	SI_	0,877	0,245	3,578	***	par_10
TA2	<---	TA_	1,006	0,105	9,542	***	par_11
TA1	<---	TA_	1,122	0,102	11,004	***	par_12
TA3	<---	TA_	1,013	0,103	9,85	***	par_13
TA4	<---	TA_	1				

Standardized Regression Weights: (Group number 1 - Default model)

			Estimate
TA_	<---	PE_	0,206
TA_	<---	EE_	-0,092
TA_	<---	FC_	0,535
TA_	<---	HM_	0,41

TA_	<---	HA_	0,058
TA_	<---	SI_	0,266
MH_	<---	TA_	0,26
WB_	<---	TA_	0,407
PE1	<---	PE_	0,985
PE2	<---	PE_	0,955
EE1	<---	EE_	0,675
EE2	<---	EE_	0,986
FC1	<---	FC_	0,816
FC2	<---	FC_	0,797
HM1	<---	HM_	0,937
HM2	<---	HM_	0,895
H1	<---	HA_	0,874
H2	<---	HA_	0,921
WB1	<---	WB_	0,715
WB2	<---	WB_	0,855
WB3	<---	WB_	0,73
MH1	<---	MH_	0,928
MH2	<---	MH_	0,877
MH3	<---	MH_	0,792
SI1	<---	SI_	0,628
SI2	<---	SI_	0,545
TA2	<---	TA_	0,754
TA1	<---	TA_	0,86
TA3	<---	TA_	0,778
TA4	<---	TA_	0,706

Covariances: (Group number 1 - Default model)

			Estimate	S.E.	C.R.	P	Label
HM_	<-->	HA_	0,7	0,096	7,311	***	par_22
FC_	<-->	HM_	0,747	0,102	7,307	***	par_23
EE_	<-->	FC_	0,112	0,037	3,034	0,002	par_24
PE_	<-->	EE_	0,571	0,109	5,24	***	par_25
FC_	<-->	HA_	0,588	0,09	6,55	***	par_29
EE_	<-->	SI_	0,155	0,064	2,435	0,015	par_31
HA_	<-->	SI_	0,206	0,063	3,279	0,001	par_32
EE_	<-->	HA_	0,194	0,046	4,258	***	par_33
e29	<-->	e30	1,018	0,175	5,809	***	par_26
e24	<-->	EE_	0,2	0,07	2,86	0,004	par_27
e19	<-->	e29	0,517	0,138	3,756	***	par_28
e17	<-->	e28	0,234	0,054	4,361	***	par_30

Model Fit Summary

CMIN

Model	NPAR	CMIN	DF	P
Default model	64	521,412	189	0
Saturated model	253	0	0	
Independence model	22	3445,033	231	0

RMR, GFI

Model	RMR	GFI	AGFI	PGFI
Default model	0,303	0,831	0,769	0,606
Saturated model	0	1		
Independence model	0,7	0,193	0,108	0,175

Baseline Comparisons

Model	NFI Delta1	RFI rho1	IFI Delta2	TLI rho2

Default model	0,88	0,851	0,924	0,904
Saturated model	1		1	
Independence model	0	0	0	0

Parsimony-Adjusted Measures

Model	PRATIO	PNFI	PCFI
Default model	0,805	0,709	0,743
Saturated model	0	0	0
Independence model	1	0	0

NCP

Model	NCP	LO 90	HI 90
Default model	232,479	178,454	294,19
Saturated model	0	0	0
Independence model	3018,677	2838,713	3205,973

FMIN

Model	FMIN	F0	LO 90	HI 90
Default model	2,228	1,344	1,032	1,701
Saturated model	0	0	0	0
Independence model	18,547	17,449	16,409	18,532

RMSEA

Model	RMSEA	LO 90	HI 90	PCLOSE
Default model	0,071	0,082	0,105	0
Independence model	0,303	0,294	0,312	0

AIC

Model	AIC	BCC	BIC	CAIC
R5R6Default model	499,479	515,229	679,545	736,545
Saturated model	420	478,026	1083,402	1293,402
Independence model	3248,677	3254,203	3311,858	3331,858

ECVI

Model	ECVI	LO 90	HI 90	MECVI
Default model	2,887	2,575	3,244	2,978
Saturated model	2,428	2,428	2,428	2,763
Independence model	18,778	17,738	19,861	18,81

HOELTER

Model	HOELTER .05	HOELTER .01
Default model	83	89
Independence model	13	13

APPENDIX C: ETHICS APPROVAL

Graduate School of Business Administration
University of the Witwatersrand, Johannesburg

Wits Business School Ethics Committee
Constituted under the University Human Research Ethics Committee (Non-Medical)

Ethics Clearance Certificate

Ethics protocol number: WBS/DB2627446/222

This certificate is only valid with a legitimate ethics protocol number and signed by the Researcher (below).

Project title	The impact of digital technologies on employees' mental health and wellbeing in financial services in South Africa
Investigator / Researcher	Mrs Eleanor Sansovini
Nature of Project	MM (Digital Business)
Decision of the Committee	Approved, provided stakeholders and participants are guaranteed confidentialty.
Issue Date of Certificate	8/29/2023
Expiry date	Date of submission of the project / research report
Chairperson	Dr Pius Oba ☎ +27 11 717 3976 +27 82 733 6587 pius.oba@wits.ac.za

Declaration by Researcher

One copy must be signed by the Researcher and returned to the Chairperson of the Wits Business School Et Committee.

I fully understand the conditions under which I am authorized to carry out the abovementioned research a guarantee to ensure compliance with these conditions. Should any departure to be contemplated from the research procedure as approved I undertake to resubmit the protocol to the Committee.

Eleanor Sansovini

Signature

29/08/2023

Date:

SAFEGUARDING THE MENTAL HEALTH OF EMPLOYEES IN THE FINANCIAL SERVICES SECTOR. (2024, February 24). *Lock Associates Group*. Retrieved from https://lochassociates.co.uk/safeguarding-the-mental-health-of-employees-in-the-financial-services-sector/

YOUR GUIDE TO MENTAL HEALTH FIRST AID AT WORK. (2024). Retrieved from https://lochassociates.co.uk/mental-health-aid-at-work/