



# **Developing a framework to assess the influence of technostress on academics' individual performance in a selected higher education institution**

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**DECLARATION**

I, **Abdul Feroz Maluleke**, declare that the thesis entitled “**Developing a framework to assess the influence of technostress on academics’ individual performance in a selected higher education institution**” is my own work and that all the sources I have used or quoted have been indicated and acknowledged using complete references.

Signature:  \_\_\_\_\_

Date : 07 September 2025

**DEDICATION**

All praise and thanks are due to Allah (The entirely Merciful) alone for granting me an opportunity, strength and ability to complete my PhD studies successfully. This doctoral work is dedicated to my sons, Umar Maluleke and Naasir Maluleke. I hope that through this accomplishment, I have modelled perseverance and ambition for your own pursuit of success in shaa Allah.

\*\*\*\*\*

To my lovely family who have supported me throughout the years, especially during difficult and testing times, you have added so much value to me and my studies.

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## **ABSTRACT**

This study aimed to develop a framework to assess the influence of technostress on individual work performance in South African higher education institutions. It also sought to determine the moderating roles of Technology Self-efficacy and Proactive Personality in this relationship. To address the objective, the study employed a quantitative research approach within a positivist paradigm, aiming to provide a comprehensive understanding of technostress and its impact on academic staff performance. Data were collected from 304 academic staff across seven campuses of Tshwane University of Technology using an online survey distributed via a fieldworker to ensure compliance with ethical standards. Simple random sampling was employed, and the data were analysed using STATA after being prepared in Microsoft Excel.

The findings revealed that technostress, defined as stress associated with the use and adoption of computer-related technologies for learning purposes, significantly affects the work performance of academic staff. High levels of technology self-efficacy were associated with better task performance despite the presence of technostress, and increases in technology self-efficacy were linked to significant reductions in counterproductive work behaviour under low and moderate levels of technostress.

Additionally, academic staff with high levels of proactive personality demonstrated consistently high performance, regardless of techno-complexity. These findings highlight that academic staff who exhibit strong self-efficacy and proactivity are less affected by stress arising from technology use. Thus, self-efficacy and proactiveness serve as critical moderating factors in mitigating the adverse effects of technostress on performance.

The study underscores several managerial implications for African higher education institutions, including the need to enhance technological infrastructure, provide comprehensive training and support, manage workloads effectively, and redesign policies to reduce the impact of technostress on academic staff. By focusing on task performance, counterproductive work behaviour, and contextual performance, this research contributes significantly to understanding technostress in African higher education. The findings offer actionable recommendations and provide a foundation

for future studies to explore tailored strategies for managing techno-overload and complexity in academic contexts.

**Keywords:** Technostress, Individual Work Performance, Technology Self-efficacy, Proactive Personality, Higher Education Institutions, South Africa, Academic Staff

## OPSOMMING

Hierdie studie het ten doel gehad om 'n raamwerk te ontwikkel om die invloed van teganostres op individuele werksprestasie in Suid-Afrikaanse hoër onderwysinstellings te evalueer. Dit het ook gepoog om die modererende rolle van tegnologie-selfdoeltreffendheid en proaktiewe persoonlikheid in hierdie verband te bepaal. Om hierdie doelwitte te bereik, het die studie 'n kwantitatiewe navorsingsbenadering binne 'n positivistiese paradigma aangeneem om 'n omvattende begrip van teganostres en die impak daarvan op akademiese personeel se prestasie te bied. Data is ingesamel van 304 akademiese personeel oor sewe kampusse van die Tshwane Universiteit van Tegnologie deur middel van 'n aanlyn-opname wat deur 'n veldwerker versprei is om voldoening aan etiese standaarde te verseker. 'n Eenvoudige ewekansige steekproefmetode is gebruik, en die data is geanaliseer met behulp van STATA nadat dit in Microsoft Excel voorberei is.

Die bevindings het getoon dat teganostres, gedefinieer as stres wat verband hou met die gebruik en aanvaarding van rekenaarverwante tegnologieë vir leerdoeleindes, 'n beduidende invloed op die werksprestasie van akademiese personeel het. Hoë vlakke van tegnologie-selfdoeltreffendheid is geassosieer met beter taakprestasie ten spyte van die teenwoordigheid van teganostres, en toenames in tegnologie-selfdoeltreffendheid is gekoppel aan aansienlike vermindering in kontraproduktiewe werkgedrag onder lae en matige vlakke van teganostres.

Verder het akademiese personeel met hoë vlakke van proaktiewe persoonlikheid konsekwent hoë prestasie getoon, ongeag die vlak van tegnologiese kompleksiteit. Hierdie bevindings beklemtoon dat akademiese personeel met sterk selfdoeltreffendheid en proaktiwiteit minder geraak word deur stres wat voortspruit uit tegnologiegebruik. Dus dien selfdoeltreffendheid en proaktiwiteit as kritieke modererende faktore in die versagting van die nadelige gevolge van teganostres op prestasie.

Die studie beklemtoon verskeie bestuursimplikasies vir Afrika hoër onderwysinstellings, insluitend die noodsaaklikheid om tegnologiese infrastruktuur te verbeter, omvattende opleiding en ondersteuning te bied, werkladings effektief te bestuur en beleide te herontwerp om die impak van teganostres op akademiese personeel te verminder. Deur te fokus op taakprestasie, kontraproduktiewe

werkgedrag en kontekstuele prestasie, dra hierdie navorsing betekenisvol by tot die begrip van teginostres in Afrika hoër onderwys. Die bevindings bied aksiebare aanbevelings en verskaf 'n grondslag vir toekomstige studies om aangepaste strategieë te ondersoek vir die bestuur van tegnologie-oortlading en kompleksiteit in akademiese kontekste.

**Sleutelwoorde:** Teginostres, Individuele Werksprestasie, Tegnologie-Selfdoeltreffendheid, Proaktiewe Persoonlikheid, Hoër Onderwysinstellings, Suid Afrika, Akademiese Personeel

## ABBREVIATIONS AND ACRONYMS

|        |                                                    |
|--------|----------------------------------------------------|
| CP     | Contextual Performance                             |
| CWB    | Counterproductive Work Behaviour                   |
| ETM    | Extended Technostress Model                        |
| ETS-ES | Educator Technology Self-Efficacy Survey           |
| HEI    | Higher Education Institution                       |
| ICT    | Information and Communication Technology           |
| IS     | Information Systems                                |
| ISTE   | International Society for Technology in Education  |
| IWP    | Independent Work Performance                       |
| LMS    | Learning Management System                         |
| MMR    | Multivariate Multiple Regression                   |
| NWU    | North-West University                              |
| PLS    | Partial Least Squares                              |
| PP     | Proactive Personality                              |
| SCT    | Social Cognitive Theory                            |
| SEM    | Structural Equation Modelling                      |
| TAM    | Technology Acceptance Model                        |
| TCI    | Technostress Creators Inventory                    |
| TMSC   | Transactional Model of Stress and Coping           |
| TP     | Task Performance                                   |
| TSE    | Technology Self-efficacy                           |
| TUT    | Tshwane University of Technology                   |
| UTAUT  | Unified Theory of Acceptance and Use of Technology |
| WTS    | Workplace Technostress Scale                       |

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## **CHAPTER ONE**

### **INTRODUCTION AND BACKGROUND**

#### **1.1 INTRODUCTION**

This chapter introduces the study by outlining the background on the influence of technostress in the higher education sector and its impact on the performance of academic staff. Over the past two decades, the adoption of information and communication technology (ICT) has significantly transformed teaching and learning within higher education institutions (HEIs). In particular, the computerisation of tasks and the broader digital transformation aimed at enhancing teaching and learning have altered academic work processes. Within the African context, such developments have contributed to the emergence of technostress among academic staff. This chapter highlights the research gap concerning technostress in African HEIs, with a specific focus on a South African university where academics increasingly encounter technostress as they adapt to digital technologies in the teaching and learning environment. This chapter also discusses the empirical and practical significance of the study.

#### **1.2 BACKGROUND, CONTEXT AND PROBLEM STATEMENT**

The workplace has undergone significant changes over the past two decades, primarily due to the adoption of ICTs and the ensuing digital transformation (McAfee, 2006). In recent years, a persistent trend of task computerisation has been observed in the higher education sector. As a result, HEIs are rapidly adopting new technologies to facilitate teaching and learning (Jena, 2015; Abo Mokh *et al.*, 2021). However, despite the many benefits of ICT in the workplace, some scholars argue that technology can have a negative impact on end users (Christian *et al.*, 2020; Pirikkalainen *et al.*, 2019; Ayyagari *et al.*, 2011) and lower productivity (Le Roux & Botha, 2021).

Technostress is a type of stress experienced by end-users in organisations due to the use of ICTs (Ahmad, 2012; Christian *et al.*, 2020). Hao *et al.* (2020) maintain that the impact of technostress can vary depending on the context; it may have either positive

or negative effects on other variables. However, there has been limited research on technostress in Africa, particularly in South Africa. Most studies on technostress have focused on employees who are constantly exposed to ICTs and related technologies. Still, this approach overlooks the impact on non-ICT users, such as academics and researchers. Therefore, this study focused on university academics facing difficulties in the higher education sector due to accelerating technological change.

With the rapid adoption of ICT across various business sectors, scholarly research into technostress in different contexts is crucial. The rise in the introduction of ICT devices and new technologies has prompted HEI institutions to shift from a teacher-centred classroom paradigm to adopting technology-enhanced learning methods (Joo, Lim & Kim, 2016; Markowitz, Laha, Perone, Pea & Bailenson, 2018). Academics' inability to cope with the introduction of ICTs into the classroom causes technostress (Abo Mokh *et al.*, 2021; Salem, 2018; Gaudio, 2017).

Previous research across various business sectors has reported the impact of technostress on work performance (for example, Marchiori *et al.*, 2019; Hsiao, 2017; Jena, 2015; Salanova, 2020). However, Penado Abilleira *et al.* (2020) and Özgür (2020) confirm that few of these studies addressed technostress in academic settings. Additionally, studies investigating technostress in educational settings have predominantly focused on students rather than academic staff members (Sharma & Gupta, 2022; Fernández-Batanero, 2021; Upadhyaya & Vrinda, 2021).

Scholars argue that the presence of technostress inhibitors, such as technical support, knowledge of ICT use and technology self-efficacy, can mitigate the occurrence of technostress (Tarafdar *et al.*, 2011; Fuglseth & Sørensen, 2014). In contrast, employees who lack digital skills and have low technology self-efficacy beliefs tend to exhibit high technostress levels, which in turn affect their ability to utilise educational technology when teaching (Kale & Goh, 2014; Ertmer & Ottenbreit-Leftwich, 2010; Cavas *et al.*, 2009). It is against this backdrop that Williams-Buffong (2021:9) argues that the lack of self-efficacy among employees hinders technology adoption and decreases work performance.

Recent years have witnessed a lack of sufficient research on technostress within higher education settings in developing countries across various contexts and cultures

(Li & Wang, 2021). Although several attempts have been made to determine the relationship between technostress and ICT adoption in higher education, very few studies have focused on academics and support staff, particularly within the African context. With most South African universities adopting online and blended learning methods, it has become crucial for universities to examine how South African university academics cope with technostress relating to their work performance.

***The problem statement of this study was to investigate the negative impact of technostress on the Individual work performance of academic staff in a selected higher education institution in South Africa and to examine the potential moderating roles of technology self-efficacy and proactive personality in this relationship.***

### **1.3 RATIONALE AND SIGNIFICANCE OF THE STUDY**

The rapid adoption of educational technologies for teaching and learning purposes in South African HEIs has raised concerns about the technostress associated with the use of these digital technologies. Moreover, although many studies have highlighted the importance and benefits of technology adoption in South African higher education, there is still a need for further research. There remains a gap in the literature on how the technostress resulting from technology adoption affects the work performance of academic staff members in HEIs. Previous research on technostress in South Africa is limited (Le Roux & Botha, 2021; Van Eck, 2005), with most studies involving computer professionals and IT consultants (Ferziani *et al.*, 2018). It is against this background that this study aimed to close the gap through the development of a framework that assesses the influence of technostress on the individual work performance of academic staff in a South African HEI. Additionally, this study explored the moderating roles of proactive personality and technology self-efficacy on the technostress–performance relationship. This study is unique because it was the first to be conducted within HEIs on this topic in the broader South African context.

The proposed framework could help HEIs understand the impact of technostress on academic staff members' performance and create strategies to manage technostress in South African HEIs. The development of a framework provides evidence-based insights that can aid HEIs in designing targeted interventions to mitigate technostress

and enhance academic staff performance. By assessing the role of proactive personality and technology self-efficacy (TSE) in mitigating technostress, this study supports data-driven decisions that can improve staff resilience to technostress through staff recruitment, policy development and training interventions. Lastly, the study equips HEI leaders with a practical model to understand the interplay between psychological factors and technology-related stress, enabling them to manage digital integration more effectively.

#### **1.4 OBJECTIVES OF THE STUDY**

The objectives of the study were formulated as follows:

##### **Primary research objective**

- The primary objective of this study was to develop a framework for assessing the influence of technostress on the performance of academic staff and to examine the moderating roles of technology self-efficacy and proactive personality in a selected higher education institution.

##### **Secondary research objectives**

- To establish the mean scores of technostress, individual work performance, technological self-efficacy and proactive personality of academic staff.
- To establish if there are differences in technostress, individual work performance, technological self-efficacy and proactive personality between genders.
- To establish if there are differences in technostress, individual work performance, technological self-efficacy and proactive personality between age groups.
- To establish if there is a relationship between technostress and individual work performance.
- To assess the moderating role of technology self-efficacy in the relationship between technostress and academic staff performance.
- To assess the moderating role of proactive personality in the relationship between technostress and academic staff performance.

## 1.5 RESEARCH QUESTIONS AND HYPOTHESES

**The primary research question was:** Can a framework be developed to explain how technostress influences academic staff performance and how technology self-efficacy and proactive personality moderate this relationship?

**The secondary research questions were:**

- What are the mean scores of technostress, individual work performance, technological self-efficacy and proactive personality among academic staff in these selected higher education institutions?
- Are there significant differences in technostress, individual work performance, technological self-efficacy and proactive personality among academic staff of different genders?
- Are there significant differences in technostress, individual work performance, technological self-efficacy and proactive personality among academic staff across age groups?
- To what extent is there a relationship between technostress and individual work performance?
- To what extent does technology self-efficacy moderate the relationship between technostress and academic staff performance?
- To what extent does proactive personality moderate the relationship between technostress and academic staff performance?

Based on the research objectives and questions, the following proposed hypotheses were tested:

- **Null Hypothesis ( $H_{01}$ ):** A framework cannot be developed to explain how technostress influences the performance of academic staff and how technology self-efficacy and proactive personality moderate this relationship.
- **Alternative Hypothesis ( $H_{a1}$ ):** A framework can be developed to explain how technostress influences academic staff performance and how technology self-efficacy and proactive personality moderate this relationship.
- **Null Hypothesis ( $H_{02}$ ):** The mean scores of technostress, individual work performance, technological self-efficacy and proactive personality among

academic staff in the selected higher education institution do not significantly differ from expected or baseline values.

- **Alternative Hypothesis ( $H_{2a}$ ):** The mean scores of technostress, individual work performance, technological self-efficacy and proactive personality among academic staff in the selected higher education institution differ significantly from expected or baseline values.
- **Null Hypothesis ( $H_{03}$ ):** There are no significant differences in technostress, individual work performance, technological self-efficacy and proactive personality among academic staff of different genders.
- **Alternative Hypothesis ( $H_{a3}$ ):** There are significant differences in technostress, individual work performance, technological self-efficacy and proactive personality among academic staff of different genders.
- **Null Hypothesis ( $H_{04}$ ):** There are no significant differences in technostress, individual work performance, technological self-efficacy and proactive personality among academic staff across age groups.
- **Alternative Hypothesis ( $H_{a4}$ ):** Among academic staff, there are significant differences in technostress, individual work performance, technological self-efficacy and proactive personality across age groups.
- **Null Hypothesis ( $H_{05}$ ):** There is no significant correlation between technostress and individual work performance among academic staff.
- **Alternative Hypothesis ( $H_{a5}$ ):** Technostress and individual work performance among academic staff are significantly related.
- **Null Hypothesis ( $H_{06}$ ):** Technology self-efficacy does not moderate the relationship between technostress and academic staff performance.
- **Alternative Hypothesis ( $H_{a6}$ ):** Technology self-efficacy moderates the relationship between technostress and academic staff performance.
- **Null Hypothesis ( $H_{07}$ ):** Proactive personality does not moderate the relationship between technostress and academic staff performance.
- **Alternative Hypothesis ( $H_{a7}$ ):** Proactive personality moderates the relationship between technostress and academic staff performance.

## 1.6 PRELIMINARY LITERATURE REVIEW

The literature review focused on the four constructs used in this study: technostress (independent variable), technology self-efficacy, proactive personality (moderating variables), and individual work performance (dependent variable).

The conceptual framework of this study is depicted in Figure 1.1.

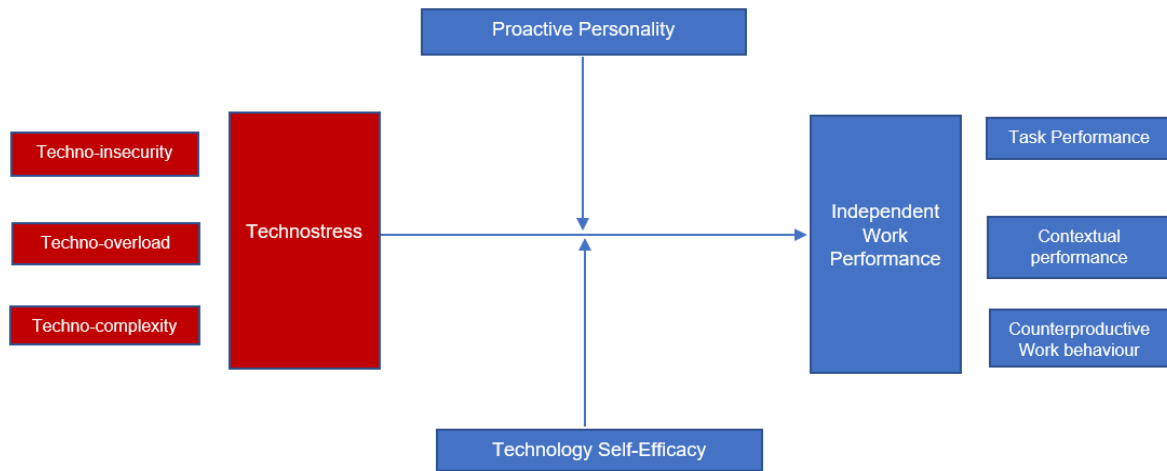


**Figure 1.1: Conceptual framework of this study**

### 1.6.1 Technostress

Technostress was originally defined as a disorder that arises when individuals struggle to cope with the introduction and use of new computer technologies in the workplace (Brod, 1984:16). This definition has since evolved. Weil and Rosen (1997), for instance, describe technostress as any negative impact on an individual's attitudes, behaviours or thoughts resulting from the use of technology. More recent scholars, including Tarafdar *et al.* (2007) and Ayyagari *et al.* (2011), define technostress as "stress that users experience as a result of their use of information systems (IS) in the organisational context".

University academics in HEIs are rapidly integrating ICT-based tools in their teaching and learning environments (Scardamalia & Bereiter, 2008). Digital tools now sit at the core of higher education because they promote both independent and group learning (Joo *et al.*, 2016; Markowitz *et al.*, 2018). At the same time, their swift rollout can place a burden on institutions and staff. Frequent ICT upgrades often trigger technostress—

work-related strain tied to technology use—among lecturers and administrators (Abo Mokh *et al.*, 2021; Gaudioso, 2017; Salem, 2018). As universities expand their digital ecosystems, levels of technostress climb and academic performance declines (Bencsik & Csinger, 2021; Li & Wang, 2021).

According to Llorens *et al.* (2011), the continuous changes brought about by scientific and technological advances over the past decades have made teaching one of the most stressful professions globally. Consequently, academics are now expected not only to integrate various educational technologies into their pedagogical practices (Graham *et al.*, 2009) but also to keep pace with the rapid and ongoing innovations within the education sector (Voet & De Wever, 2017; Tarus *et al.*, 2015). Although academics generally perceive technology as a valuable tool for lesson preparation, content delivery and student engagement, many academics lack the requisite skills and competencies to use it effectively within the teaching and learning environment (Chen, 2015; Munyengabe *et al.*, 2017).

The struggle to integrate and utilise technological tools during instruction has been linked to several adverse outcomes, including burnout, exhaustion, role conflict, decreased job satisfaction, role overload and diminished work performance (Ragu-Nathan *et al.*, 2008; Ayyagari *et al.*, 2011; Tarafdar *et al.*, 2007). This inability to adapt to the rapid proliferation of educational technologies contributes to the emergence of technostress. While researchers have proposed diverse conceptualisations of technostress, this study adopted the five-dimensional framework advanced by Ragu-Nathan *et al.* (2008) and Marchiori *et al.* (2019), namely, techno-overload, techno-invasion, techno-complexity, techno-insecurity and techno-uncertainty.

In the context of this study, *techno-overload* refers to situations where ICT usage compels academic staff to work both faster and longer. *Techno-complexity* relates to the challenges that arise when using ICT tools which require the acquisition of new skills due to their complexity. *Techno-uncertainty* is characterised by a sense of unease stemming from ambiguous or unrealistic expectations associated with ICT integration. Lastly, *techno-insecurity* refers to feelings of vulnerability among academics who fear being replaced by technology or losing their jobs due to the adoption of ICT.

### 1.6.2 Technology self-efficacy

Integrating technology into the classroom offers an opportunity for effective student engagement in spatial intelligence and stimulates conceptual comprehension (Bell, Maeng & Binns, 2013; Martin, Shaw & Daughenbaugh, 2014). Technology self-efficacy is a social cognitive construct that is primarily rooted in Bandura's (1977) theory which defines self-efficacy as "intellectual activity by which one develops one's beliefs about one's ability to achieve a certain level of accomplishment". Integrating educational technologies into higher education is a complex process that necessitates specific skills to successfully utilise these technologies (Nawaz, Awan & Ahmad, 2011). However, scholars argue that the importance of technology self-efficacy beliefs in integrating ICTs into teaching and learning is self-evident (Kale & Goh, 2014:49; Zhang *et al.*, 2023). Technology self-efficacy beliefs are key to successfully integrating technologies for pedagogical purposes (Zhang *et al.*, 2023).

According to Clipa, Delibaş and Măță (2023), technology self-efficacy refers to individuals' belief in their ability to use technology effectively for teaching purposes. Existing literature has established a strong relationship between technology-related self-efficacy beliefs and academic success (Travis *et al.*, 2020; Affuso *et al.*, 2017). It is therefore essential to assess the technology self-efficacy of academic staff to promote the effective integration of educational technologies within higher education institutions (Moore-Hayes, 2011; Kale & Goh, 2014). Other scholars posit that TSE could contribute to poor work performance among employees in higher education (Williams-Buffonge *et al.*, 2021:9).

### 1.6.3 Proactive personality

Proactive personality was initially conceptualised in the early 1990s to describe the change in behaviour among employees in the organisation related to workplace norms (Bateman & Crant 1993). In essence, proactive personality refers to individuals' ability to engage in the roles assigned to them and their willingness to influence others (Hung *et al.*, 2015). Proactivity is viewed as a highly significant behaviour in promoting optimal work performance in contemporary organisational settings. According to Crant *et al.* (2017), the proactive personality has become increasingly important in management studies and organisational behaviour, as more organisations adopt a

range of technologies to induce optimal work performance. This is further supported by Cuadrado *et al.* (2024), who assert that the proactive personality is a crucial trait that needs to be investigated in organisational behaviour. According to Tiwari (2021) and Hung, Chen and Lin (2015), proactive personality plays a crucial role in how employees react to technostress and its effect on work performance. In ICT-enabled environments, having a proactive personality has a direct bearing on how employees perform their daily tasks and on productivity (Philip & Kosmidou, 2023; McCormick *et al.*, 2019).

In the higher education context, proactive employees are reported to have a lower incidence of technostress: proactivity enables them to cope with the stress (Li & Wang, 2021). Some scholars highlight the significance of the proactive trait among employees who work in ICT-enabled higher education environments (Zhang, Chen & Zheng, 2014). Using the multidimensional transaction theory, Sharma and Gupta (2023) found that the proactive personality trait played a critical role in advancing cognitive and coping strategies in dealing with technostress in higher education environments. Another benefit of employing proactive individuals is that they tend to positively influence their colleagues, which can have a positive effect on work performance in the organisation (Ye, 2018). It is therefore crucial for managers to hire employees with moderate to high proactivity to ensure the successful integration of ICTs in the workplace (Wang *et al.*, 2017).

#### **1.6.4 Individual work performance**

Individual work performance (IWP) refers to the measurement of a particular employee's effectiveness in fulfilling his or her work-related duties (Koopmans *et al.*, 2011). IWP measures how well employees perform their job tasks individually. In recent years, the assessment of performance in organisational behaviour has shifted from a group-centric to an individual perspective as demands reshaped workplace norms (Ramos-Villagrasa *et al.*, 2019). However, there is no agreed-upon definition that theoretically captures all dimensions of IWP within the context of organisational behaviour. For example, Koopmans *et al.* (2011) initially conceptualised four dimensions to measure IWP: task performance, contextual performance, adaptive performance and counterproductive work behaviour. According to Carpinì, Parker and Griffin (2017), scholars measured IWP differently based on their theoretical lenses on

what constituted performance. However, each assessment focused on the performance of a single employee, rather than a group. As such, this study adopted the IWP framework proposed by Koopmans *et al.* (2014), which conceptualises IWP as a second-order construct comprising three first-order reflective dimensions: task performance, contextual performance and counterproductive work behaviour.

Measuring IWP in the higher education sector has become crucial, due to the dynamic nature of pedagogy and organisational strategies (ChaaCha & Oosthuysen, 2023) as well as the rapid surge in ICT adoption among HEIs, given the influence of ICT technologies on organisational success (Deng, Duan & Wibowo, 2023) and how employees perceive their work (Herzberg *et al.*, 2011). In recent years, numerous studies have highlighted the need to measure IWP across the education sector to capture its multifaceted nature, especially in terms of academic staff performance (Koopmans *et al.*, 2014; Li & Wang, 2021). Furthermore, the assessment of IWP has been instrumental in understanding productivity and technostress in other fields of study (La Torre, De Leonardis & Chiappetta, 2020; Taris & Schaufeli, 2018).

#### **1.6.5 Relationship between technostress, technology self-efficacy, proactive personality and individual work performance**

Technostress is commonly associated with anxiety, fatigue, dissatisfaction and overwork, all of which adversely affect employee performance (Wang & Li, 2019). Technostress has a negative influence on employee performance in organisational settings (Tiwari, 2020; Tarafdar, Pullins & Ragu-Nathan, 2015). According to Bourlakis, Nisar and Prabhakar (2023), the prevalence of technostress has a significant impact on employee work performance in educational contexts. These findings are echoed by Li and Wang (2021), who highlight that technostress negatively influences the work performance of employees in higher education institutions. In the absence of technostress inhibitors, HEIs continue to witness declining work performance as a result of technostress within the employee workforce (Wang & Li, 2019).

As many organisations, particularly HEIs, continue to adopt ICTs to promote productivity in the post-pandemic era, scholars have highlighted the importance of a proactive personality in mitigating the occurrence of technostress (Hung *et al.*, 2015). Previous research emphasised the significance of the proactive trait in moderating

technostress influence on employee performance. According to Philip and Kosmidou (2023), the proactive personality trait moderates the relationship between technostress and work performance in ICT-enabled workplaces. Rohma and Zakiyah (2021) assessed the role of proactive personality on technostress strains among individuals and its effect on work performance. They found that proactive personality fully moderated technostress-related strain on work performance (Rohma & Zakiyah, 2021; Tiwari, 2020). Furthermore, other scholars reported that proactive personality mitigated technostress creators, which have a negative impact on job outcomes (Srivastava, Chandra & Shirish, 2015). Therefore, this study hypothesised that proactive personality moderated the relationship between technostress and academic staff performance in the higher education context.

Many scholars argue that employees who work in ICT-enabled environments could reduce the impact of technology stress through self-efficacy beliefs. Technology self-efficacy emanates from Bandura's (1997) theory that the self-beliefs of individuals have a strong effect on their behaviour and job outcomes. Shu, Tu and Wang (2011) advance this argument and define technology self-efficacy as the beliefs that individuals have in their ability to deal with ICT technologies in the workplace. Moreover, research indicates that staff with high TSE report lower technostress and perform more effectively (Ibrahim *et al.*, 2024). TSE also changes how technostress affects performance, with confident users experiencing lower strain and higher productivity (Yener, Arslan & Kiliç, 2021)

## **1.7 DEFINITION OF CONCEPTS**

- **Technostress**

Technostress refers to the strain employees experience when they rely on information systems in their daily work (Tarafdar *et al.*, 2007; Ayyagari *et al.*, 2011).

- **Technostress inhibitors**

Situational resources that ease this strain are called technostress inhibitors; they relieve the pressure created by technology use (Ragu-Nathan *et al.*, 2008).

- **Technology self-efficacy**

Technology self-efficacy captures academics' belief in their capability to work productively with digital tools (Wang, Ertmer & Newby, 2004:231).

- **Proactive personality**

A proactive personality is a stable trait, marked by the tendency to initiate change rather than wait for it and to act on opportunities to shape the environment (Bateman & Crant, 1993).

- **Individual work performance**

Individual work performance refers to the degree to which a person fulfils assigned job tasks and meets established standards (Jena, 2015).

## **1.8 RESEARCH PHILOSOPHY**

This study adopted a positivist research paradigm. Brand (2009:432) defines positivism as “a belief system arising out of practices in the natural sciences which assume that matters that are the subject of research are susceptible of being investigated objectively and that their veracity can be established with a reasonable degree of certainty”. This study employed a positivist paradigm to investigate whether technostress affected work performance. The positivist paradigm is ideal for business studies, where hypothesis verification is the foundation of the study (Brand, 2009:433).

## **1.9 RESEARCH METHODOLOGY**

This study employed a quantitative research methodology to investigate the influence of technostress on IWP and the moderating roles of TSE and proactivity on the technostress–performance relationship. Quantitative research is a method that involves collecting and analysing structured data, usually represented numerically (Khoa, Hung & Hejsalem-Brahmi, 2023). The quantitative method was chosen for its suitability in addressing the aim of this study, which was to test relationships between multiple variables (Goertzen, 2017). Furthermore, the quantitative methodology has, in the past, been deemed the research method most suited to assess technostress in the workplace (Rolon, 2014; Saim, Rashid & Ma'on, 2021).

### **1.10 RESEARCH DESIGN**

This research adopted a cross-sectional research design to assess the influence of technostress on academic staff performance at a higher education institution. A research design guides researchers in gathering and analysing data to answer research questions (Quinlan *et al.*, 2019). The correlational design is suitable for research studies that aim to explore relationships between variables (Dziak, 2020). Furthermore, given that this study investigated the moderating effect of two variables (i.e., TSE and proactive personality), a cross-sectional design was deemed suitable as data could be collected at a specific point in time to ensure efficiency.

### **1.11 POPULATION**

For the study's findings to be valid, the researcher must determine the target population that will partake in the survey before the commencement of data collection (Hossan, Dato' Mansor & Jaharuddin, 2023). In this research the target population comprised academic staff employed at a South African university of technology. Clearly defining the research population ensures that the findings of the study are valid (Hossan, Dato'Mansor & Jaharuddin, 2023).

### **1.12 SAMPLING METHOD**

Simple random sampling was used to select respondents, ensuring that each lecturer had an equal chance of inclusion and that there was balanced representation from all faculties (Singh & Masuku, 2014). This method suits a single-site survey because it minimises selection bias while remaining practical.

### **1.13 SAMPLE SIZE**

The sample size has a significant impact on the statistical power of any quantitative inquiry. Fowler and Lapp (2019) recommend computing sample needs early, using confidence levels and the study's aims. Following their advice, the project utilised Raosoft software with a 95% confidence level and determined a sample size of 304 participants. This figure exceeds the 100–150 cases generally advised for structural equation modelling, providing enough data for the planned analyses (Adhikari, 2021).

### 1.14 DATA COLLECTION INSTRUMENTS

To attain the research objectives, the study utilised existing and validated instruments to measure the stated goals. To measure the independent variable (technostress), the study employed the instrument developed by Tarafdar *et al.* (2007) and amended by Chen (2015). The revised instrument, as adapted by Chen (2015), is particularly relevant because it is well-suited to the context of the research topic and the current study's research objectives. Chen's (2015) version was adapted to assess technostress in the context of a developing country (i.e., China) which has similar challenges and contexts as South Africa, where this study was undertaken (Le Roux & Botha, 2021:5). The technostress instrument consists of 23 Likert-scale items (Tarafdar, 2007; Chen, 2015).

The assessment of the dependent variable (i.e., IWP) was conducted using the Individual Work Performance Questionnaire (IWPQ), an existing and validated instrument developed by Koopmans *et al.* (2014). The IWPQ consists of three sub-constructs: task performance, contextual performance and counterproductive work behaviour. The Individual Work Performance Questionnaire (IWPQ) contains 18 statements rated on a five-point Likert scale and shows sound face and structural validity in academic settings (Koopmans *et al.*, 2014).

The study relied on the Educator Technology Self-Efficacy (ETSE) scale to assess TSE. This 30-item measure, developed by Gentry *et al.* (2014), is widely used in education research and reports a Cronbach's alpha of .96, signalling excellent internal consistency.

To assess proactive personality, the study used the Proactive Personality Scale (PPS). The PPS comprises 17 Likert-scale items that measure the degree to which individuals demonstrate proactiveness in initiating change in their work environment (Bateman & Crant, 1993). The PPS showed strong reliability and validity measurement in previous research studies (Trifiletti *et al.*, 2009; Crant, Hu & Jiang, 2016; Teye-Kwadjjo & De Bruin, 2022). Therefore, the final scale instrument administered to the respondents contained 32 items to measure the variables under study.

### 1.15 RELIABILITY OF MEASURING INSTRUMENTS

According to Mohamad *et al.* (2015), determining the reliability of a research instrument before the commencement of data collection is crucial. Researchers utilise several approaches to assess the reliability of a research instrument (Knapp & Mueller, 2010). In this study the reliability of the instruments adopted was assessed through the use of Cronbach's alpha coefficient. Scholars highlight the suitability of Cronbach's alpha in educational research (Zakariya, 2022). Cronbach's alpha is a reliability measurement that evaluates the consistency of items in a scale and how well it measures the underlying construct (Ahmad *et al.*, 2024; Fraenkel *et al.*, 2015). Cronbach's alpha is reported as a single value between 0 and 1, with higher values indicating greater internal consistency or reliability of a measurement instrument. Table 1.1 presents a summary of reliability findings by the developers and users of the scales adopted in this study. As indicated, all the scales utilised in this study exceeded the 0.70 Cronbach's alpha benchmark, indicating that the scales were reliable in assessing the objectives under study.

**Table 1.1: Reliability findings by the developers of the scales**

| Scale                             | Authors                                                | Items     | Cronbach's alphas |
|-----------------------------------|--------------------------------------------------------|-----------|-------------------|
| Techno-Overload                   | Fuglseth and Sørenbø (2014)<br>Jena and Mahanti (2014) | 6         | 0.88<br>0.83      |
| Techno-Invasion                   | Jena and Mahanti (2014)                                | 3         | 0.87              |
| Techno-Complexity                 | Jena and Mahanti (2014)                                | 5         | 0.82              |
| Techno-Insecurity                 | Jena and Mahanti (2014)                                | 4         | 0.78              |
| Techno-Uncertainty                | Nimrod (2018)<br>Jena and Mahanti (2014)               | 5         | 0.87<br>0.83      |
| <b>Technostress scale</b>         |                                                        | <b>23</b> |                   |
| Task Performance (TP) scale       | Mayangsari (2020)<br>Zeglat and Janbeik (2019)         | 6         | 0.70<br>0.78      |
| Contextual Performance (CP) scale | Mayangsari (2020)<br>Zeglat and Janbeik (2019)         | 6         | 0.71<br>0.76      |

| Scale                                                               | Authors                                              | Items     | Cronbach's alphas |
|---------------------------------------------------------------------|------------------------------------------------------|-----------|-------------------|
| Counterproductive Work Behaviour (CWB) scale                        | Mayangsari (2020)                                    | 6         | 0.78              |
| <b>Individual Work Performance Scale</b>                            |                                                      | <b>18</b> |                   |
| Facilitate and Inspire Student Learning                             | Saville and Foster (2021)<br>Simsek and Yazar (2016) | 6         | 0.70<br>0.83      |
| Design and Develop Digital-Age Learning Experiences and Assessments | Saville and Foster (2021)<br>Simsek and Yazar (2016) | 6         | 0.70<br>0.87      |
| Model Digital-Age Work and Learning                                 | Saville and Foster (2021)<br>Simsek and Yazar (2016) | 6         | 0.70<br>0.77      |
| Promote and Model Digital Citizenship and Responsibility            | Saville and Foster (2021)<br>Simsek and Yazar (2016) | 6         | 0.70<br>0.78      |
| Engage in Professional Growth and Leadership                        | Saville and Foster (2021)<br>Simsek and Yazar (2016) | 6         | 0.70<br>0.85      |
| <b>Technology Self-Efficacy Scale</b>                               |                                                      | <b>30</b> |                   |
| All items on the scale                                              | Gentry <i>et al.</i> (2014)                          |           | 0.82              |

### 1.16 DATA COLLECTION

Data collection in this study was conducted using Microsoft Forms, a modern and efficient tool for disseminating the online survey link to collect data from the respondents. To comply with the ethical considerations of research and to enhance confidentiality, the human resources (HR) directorate office of the institution under study was responsible for distributing the survey link to academic staff members throughout the institution. The survey link was accompanied by the ethical clearance letter and informed consent letter, which highlighted the voluntary participatory nature of the research and respondents' right to withdraw from the study at any given point.

### **1.17 DATA CODING AND ANALYSIS**

Data analysis was done via the STATA and Statistical Package for the Social Sciences (SPSS) programmes. The study used descriptive statistics to measure the central tendency regarding the data collected from the respondents. Demographic data were displayed in visualisation format, whilst categorical variables were reported in percentages and frequencies. The study then used multivariate analysis to assess the relationships between technostress, IWP, proactive personality and TSE. The study used structural equation modelling (SEM) and partial least squares (PLS) to conduct the multivariate analysis. The instruments were tested using factor analysis, confirmatory factor analysis (CFA) and exploratory factor analysis (EFA). The findings indicated a good model fit for some items of the scales, paving the way for the reduction of items for further analysis. The study found that the model did not provide a good fit, preventing it from proceeding with SEM analysis. Therefore, the study employed multivariate multiple regression (MMR) to assess the moderating roles of proactive personality and TSE on the impact of technostress on the work performance of academic staff. According to Cheung *et al.* (2021), the MMR can capture complex relationships between multiple variables simultaneously. Additionally, the MMR is regarded as a suitable approach for analysing the relationship between various variables and moderators.

### **1.18 ETHICAL CONSIDERATIONS**

As discussed above, the data for the current study were collected through an online survey instrument. The chief information officer (CIO) of the research site was approached for permission to serve as the gatekeeper for conducting research among academic staff across the institution. Furthermore, ethical clearance was sought from the Economic and Management Sciences Research Ethics Committee (EMS-REC) of North-West University (reference: NWU-00609-23-A4) and the University of Technology's research ethics committee (reference: REC/2023/05/011) to ensure that the study adhered to all relevant ethical considerations. The researcher adhered to all stipulated ethical considerations and ensured that no harm was inflicted on any of the respondents.

### 1.19 OUTLINE OF THE DISSERTATION

The chapters in this study are organised as follows:

- **Chapter 1** introduces the research topic and provides the background of and motivation for the study. The chapter also formulates the research objectives and specifies the methodology employed to address them.
- **Chapter 2** reviews current scholarship on technostress, work performance, technology self-efficacy and proactive personality. It highlights how self-efficacy and proactivity moderate the effects of technostress, identifying gaps that this study aimed to address.
- **Chapter 3** presents the research methodology and justification for the adopted research design and its appropriateness to address the research objectives. Furthermore, this chapter outlines the target population and sampling strategy adopted to recruit the respondents.
- **Chapter 4** presents a detailed analysis of the findings of the study and the implications of these findings in the higher education context.
- **Chapter 5** concludes the study by summarising the key findings, offering practical recommendations and identifying areas for future research.

### 1.20 SUMMARY

Integrating ICTs in the South African higher education system offers numerous benefits and challenges. A prominent challenge is the prevalence of technostress among academics, which refers to a condition in which academics struggle with the use of ICTs during their pedagogical endeavours. The IWP of academic staff across HEIS in Africa is declining due to technostress, as staff members struggle with the integration of ICTs. This study, therefore, hypothesised that proactive personality and TSE might serve as moderators, reducing the prevalence and influence of technostress on the work performance of academic staff within HEIs. As such, this study aimed to develop a framework to assess the impact of technostress on the performance of academic staff at a higher education institution. The chapter also presented the methodology adopted to achieve the stated objectives. The chapter concluded by highlighting the significance of the study. The next chapter presents a review of the literature in this field.

## **CHAPTER 2:**

### **LITERATURE REVIEW OF TECHNOSTRESS, INDIVIDUAL WORK PERFORMANCE, TECHNOLOGY SELF-EFFICACY AND PROACTIVE PERSONALITY**

#### **2.1 INTRODUCTION**

The primary aim of this study was to develop a comprehensive framework that elucidates the multifaceted nature of technostress and its potential impact on the performance of academic staff. This literature review examines the current discourse on the relationship between technostress and individual work performance (IWP). Specifically, this chapter discusses the role of technostress in work performance within an academic context. The chapter also analyses the moderating effect of proactive personality and technology self-efficacy (TSE) on the influence of technostress on performance. It explores the definition of technostress and its relationship to existing frameworks. The chapter further discusses the framework related to TSE and proactivity, and how this can reduce technostress formation in higher education, as institutions of higher learning struggle to integrate technology for teaching and learning purposes.

#### **2.2 TECHNOSTRESS**

The Fourth Industrial Revolution has accelerated the spread of digital technologies across sectors. Adoption promises gains in speed, reach and coordination. It also introduces new stressors, as employees struggle to navigate complex systems to meet their goals (Dutta & Mishra, 2024). Research has examined these tensions for two decades under the label technostress (Tarafdar *et al.*, 2015). Early studies framed the issue as stress linked to computers and ICTs and its effect on employee well-being (Borle *et al.*, 2021). Recent work widens the scope to technology use across roles and industries, with attention to information overload, time pressure and control problems (Rohwer *et al.*, 2022; Raveendhran & Fast, 2019).

Initial definitions were broad. Authors used one term for different phenomena, such as technophobia and techno addiction, which blurred boundaries in measurement and practice (Nimrod, 2018). As evidence grew, definitions expanded beyond computers

to include mobile devices, platforms and integrated systems in varied contexts (Marsh, Vallejos & Spence, 2022). The Transactional Theory of Stress offered an early lens. It holds that outcomes depend on appraisal and coping. Technology use can lead to strain or to challenge states that energise action (Lei & Ngai, 2014). In this spirit, technostress reflects a perceived imbalance between situational demands and individual capacity to respond (Tarafdar *et al.*, 2019).

Contemporary accounts adopt a holistic view. They situate technostress at the intersection of person, technology and environment. Links appear with job satisfaction, individual work performance, work-life balance and burnout (La Torre *et al.*, 2019; Nimrod, 2018; Vailati Riboni *et al.*, 2020). Scholars also test interventions that support digital well-being, which point to the need for practical strategies in settings with rapid technology uptake. In the present study, technostress is defined as stress experienced due to the use of information and communication systems and technologies (Tarafdar *et al.*, 2019; Chen & Muthitacharoen, 2016). This definition accepts both aversive and energising pathways. Stress is not inherently negative or positive. Its effects depend on appraisal, resources and context (Webster *et al.*, 2011; Lei & Ngai, 2014).

Technostress is best treated as multidimensional. Evidence shows cognitive, emotional and behavioural facets that vary across tasks and roles (Sharma & Gupta, 2023). The construct also includes physiological responses. Studies report elevated heart rate, musculoskeletal strain and disturbed sleep linked to intensive or poorly designed technology use (Nimrod, 2018; Abd Aziz & Yazid, 2021; Fischer & Riedl, 2017). These findings underscore health risks alongside performance risks.

The work environment shapes both exposure and response. Policy choices, support practices, interface design and workload norms all influence the appraisal of digital demands. Organisational and social contexts, therefore, feature as causes and as buffers in current models (Kot, 2022; Wang, Ding & Kong, 2023; Nayak & Budhwar, 2022). This shift moves technostress from a purely individual issue to a systemic concern that involves design, training and culture.

Overall, the literature depicts technostress as a dynamic state that arises from daily interactions with technology. The state varies based on task demands, personal resources and environmental support. It links to key outcomes in well-being and

performance. It also responds to targeted interventions. These points motivate the present focus on academic staff and the conditions that shape their experience of digital work. The goal is precise definition, sound measurement and evidence that informs action in higher education.

### **2.2.1 Theoretical foundations of technostress**

A coherent theoretical base helps explain why digital systems strain some employees and support others. Four theories provide this base for technostress. These are the Foundational Theory of Technostress, the Transactional Model of Stress and Coping, the Technology Acceptance Model, and Social Cognitive Theory. Together, they describe how people appraise digital demands, form beliefs about technology and draw on personal and social resources. They also situate these processes in organisational settings where policies and norms shape daily experience.

Brod introduced technostress as a form of stress that arises when people struggle to adapt to computer technologies at work (Brod, 1982). Later reviews describe the exact mechanism in broader terms. When new systems arrive, some users experience strain because the skills, time or support they have do not match the demands that technology imposes. Studies report that this adaptation gap triggers technostress during periods of rapid digitisation (Urukovičová *et al.*, 2023). Early psychology work also recorded physical impacts. Fatigue, restlessness, headaches and poor coping appeared where visual display units and computerised workflows dominated daily tasks (Mardale *et al.*, 2024).

The Transactional Model of Stress and Coping explains these patterns through appraisal and coping cycles. Individuals judge whether technology-related demands threaten goals or exceed resources. They then select coping responses that can be problem-focused or emotion-focused (Lazarus & Folkman, 1984). In a digital setting, primary appraisal labels a new platform as a challenge or a hindrance. Secondary appraisal weighs skills, time and support. Maladaptive coping amplifies strain and harms performance. Supportive resources and training buffer strain and protect performance.

The Technology Acceptance Model links technostress to beliefs formed about tools. Perceived usefulness and perceived ease of use drive behavioural intention and actual

use (Davis, 1989). Low ease of use increases effort and time pressure, which aligns with common technostress creators. High usefulness without support can still overload users. Balanced design, training and user involvement shift beliefs in a favourable direction and reduce strain during adoption.

Social Cognitive Theory adds a resource perspective: self-efficacy, outcome expectations and observational learning shape behaviour under digital demands (Bandura, 1986). High technology self-efficacy supports adaptive coping. It also improves the odds that challenge appraisals dominate threat appraisals. Observing competent peers lowers anxiety and builds mastery. These pathways explain why proactive personality and technology self-efficacy often moderate links between technostress and work outcomes.

Theories also point to context. Organisational rules, workload design and social norms influence appraisal, beliefs and coping. Poorly configured systems, inadequate support and frequent changes increase strain. Clear procedures, responsive support and realistic timelines reduce it. In short, technostress is not only an individual reaction, but also a product of organisational choices.

Taken together, the four theories describe a whole chain. Digital demands arrive. People appraise those demands. Beliefs about usefulness and ease shape use. Personal resources enable coping and learning. Context amplifies or buffers these steps. This chain accounts for both negative and positive outcomes. It also integrates psychological and organisational processes that matter for individual work performance in academic settings. The present study drew on these theories to specify constructs, select measures and frame hypotheses about technostress and performance among academic staff (Brod, 1982; Lazarus & Folkman, 1984; Davis, 1989; Bandura, 1986; Urukovičová *et al.*, 2023; Mardale *et al.*, 2024).

Technological advancements have brought numerous benefits to society, but have also introduced new challenges and stressors. The rapid proliferation of information and communication technologies (ICT) in various industries has resulted in numerous challenges for individuals. During the COVID-19 pandemic, many employees experienced technostress due to the adoption of ICT in the workplace (Camacho & Barrios, 2022). The technostress phenomenon was first studied in the early 1980s.

Initially, the concept of technostress was associated with the automation of the workplace, and it was only later that the term was conceptualised to encompass the stress that employees experience due to ICT use in the workplace (Harahap *et al.*, 2023). Furthermore, prior studies on the technostress phenomenon primarily focused on the introduction of computers in organisations and the profound impact of this introduction. Researchers during this time explored the relationship between computer use and job stress to understand the negative consequences of technology adoption in the workplace (Salazar-Concha, Ficapal-Cusí, Boada-Grau & Camacho, 2021). Sharma and Gupta (2023) advanced this concept and contributed to early research recognising technostress as mainly due to issues such as information overload, role ambiguity and a lack of control. One of the key contributors to the field of technostress was Craig Bod, who coined the term “technostress” in 1984 to describe the psychological strain caused by new computer systems in the workplace (Brod, 1984). Salo *et al.* (2022) emphasise that technostress arises from the interaction between individuals and technology, particularly when technology surpasses users' ability to cope effectively. Brod's work is highly regarded in recent literature, particularly within the social sciences spectrum. Over the last two decades, technostress has gained significant traction, and scholars have begun examining its impact in various contexts beyond the workplace (Talib, Jusoh, Razali & Awang, 2022). The expansion of personal technologies, including smartphones, social media platforms and other digital devices, has raised concerns about the impact of technology on individuals' daily well-being. The progression of research indicates that scholars increasingly recognise that technostress encompasses a range of dimensions and effects (Nastjuk *et al.*, 2024). Organisations deploy digital systems to improve efficiency and reach. This shift creates new demands on employees. Studies show that structured organisational support and targeted training reduce adverse effects linked to technology use (Dutta & Mishra, 2024; Rohwer *et al.*, 2022).

The Transactional Model of Stress and Coping explains technostress as a dynamic interaction between person and environment. Individuals appraise technology-related demands, judge available resources and select coping responses. These socio-psychological processes shape strain and adaptation over time (Lazarus & Folkman, 1984). Personal dispositions and learned coping styles matter. They influence whether employees experience digital demands as a threat or a challenge and whether they

engage in problem-focused or emotion-focused strategies (Lazarus & Folkman, 1984). Context also matters. Evidence shows that organisational pace of change, support practices and workload design shape exposure and responses to technostress (Çini, Erdirençelebi & Akman, 2023).

The broader Transactional Theory of Stress and Coping advanced this view by rejecting stimulus-only accounts of stress. It placed appraisal and coping at the centre of the stress process and highlighted the continuous exchange between person and environment (Lazarus, 1966; Lazarus & Folkman, 1984). Workplace research linked role overload and role conflict to strain within this framework, which helps explain pressure in technology-intensive settings (Rizzo *et al.*, 1970; Ivancevich & Matteson, 1980). The model has limits for technostress. Digital contexts introduce features like information overload, constant connectivity and rapid interface change, which the original framework does not specify in detail. It also provides little guidance on technology-specific coping tactics (Ayyagari, Grover & Purvis, 2011). The model predates contemporary platforms, which reduces its precision for current digital dynamics. Scholars recommend complementary models to capture technology-specific mechanisms, while retaining the appraisal and coping core (Ayyagari *et al.*, 2011).

The Technology Acceptance Model offers a second lens. It explains adoption through perceived usefulness and perceived ease of use, which shape intention and actual use (Davis, 1989; Davis, Bagozzi & Warshaw, 1989). TAM is often used to study acceptance, not strain. It focuses on individual beliefs and does not incorporate organisational stressors or socio-cultural pressures in detail. Studies note that technostress includes psychological and physiological effects tied to workload, time pressure and control, which sit outside the narrow acceptance focus of TAM (Taherdoost, 2018; Alshurafat, Al Mawali & Al Shbail, 2023; Kristadi & Sucahyo, 2016; Pflügner, Maier & Weitzel, 2021). TAM remains helpful in understanding belief formation about tools, yet it does not fully explain the stress process.

Social Cognitive Theory (SCT) provides a third perspective. It highlights self-efficacy, outcome expectations and social learning as drivers of behaviour under digital demands. Higher technology self-efficacy supports adaptive coping and sustained effort during technology adoption (Bandura, 1986). Applied studies show that

strengthening teachers' beliefs in their ability to use information and communication technologies helps reduce technostress in education settings (Harahap, 2015). SCT, therefore, links organisational interventions to individual resources that buffer strain.

These theories converge on practical implications. Organisations should build capability through training tied to actual workflows, provide responsive support during rollouts and pace change to match resource availability. They should also invest in self-efficacy through modelling, guided practice and feedback. These steps address appraisal, beliefs about tools and personal resources at the same time, which lowers technostress risk while supporting performance (Lazarus & Folkman, 1984; Davis, 1989; Bandura, 1986; Çini *et al.*, 2023; Ayyagari *et al.*, 2011).

Sellberg and Susi (2014) propose a redefinition of technostress, explaining that the SCT can emphasise the need for a broader perspective on human-technology interaction. This is further supported by Yener, Arslan and Kiliç (2021), who found that the social aspect of work performance was greatly influenced by technostress. In a comprehensive literature review study, Mahapatra (2018) identified the negative impact of technostress on job outcomes and the difficulty employees face in coping with new technologies. Mahapatra (2018) posits that a plethora of research has utilised the SCT to explain how technostress creators negatively impact various job outcomes in organisations. In a study involving employees across six organisations, Stana (2021) highlighted the role of sociological mechanisms behind technostress formation, emphasising the role of the social environment in technostress research.

Against this backdrop, this study adopted the SCT as the theoretical framework for understanding how technostress influences work performance within an organisational context. Furthermore, the SCT posits that individuals learn by observing others. In the context of technostress, Sellberg and Susi (2014) highlight the role of observation in shaping behaviours and reactions to technology. As such, SCT provides a lens through which to understand how individuals model their responses to technology-related stressors based on the experiences of their colleagues. It is also crucial to mention that the SCT strongly emphasises self-efficacy, which is the belief in one's capability to organise and execute the courses of action required to manage stressful situations (Bandura, 1986).

### 2.2.2 Outcomes of technostress

Technostress creators refer to the various factors or elements within the technological environment that contribute to the experience of technostress among individuals who use information and communication technologies (ICTs) (Harris *et al.*, 2022). As discussed earlier, technostress, at its essence, represents the psychological and physiological strain that results from the use of technology, particularly in professional contexts. The conceptualisation of technostress creators (often referred to as TSC) encompasses a broad range of latent second-order constructs that can lead to stress and strain in individuals' work lives (Sharma & Gupta, 2023). The earliest prominent conceptualisation of technostress creators appeared in the works of Tarafdar *et al.* (2007). Tarafdar *et al.* (2007) found that technostress was displayed behaviourally and psychologically in the following five dimensions: techno-overload, techno-invasion, techno-complexity, techno-insecurity and techno-uncertainty. Tarafdar's dimensions were widely accepted by other leading scholars in the technostress field, such as Ragu-Nathan *et al.* (2008) and Chen (2015), who explained that technostress creators could either be manifest conditions (conditions that create strain) or mitigating conditions (conditions that mitigate technostress – techno-inhibitors).

Technostress dimensions describe the specific stressors linked to technology use at work. They arise when digital systems change how people access information, communicate and complete tasks. Everyday stressors include information overload, complex or poorly designed systems and pressure to remain constantly connected to corporate platforms and devices (Rohwer *et al.*, 2022). These pressures disrupt attention and decision-making. They also increase fatigue during routine work.

Recent studies have added more detail. Employees face continual learning demands as systems update. They must adapt to frequent upgrades. They troubleshoot recurring technical faults while their inboxes and collaboration tools generate more information than they can process in a typical day. Many roles also expect ongoing connectivity beyond office hours (Yener *et al.*, 2025). These conditions increase strain and reduce recovery time.

Interaction effects matter. When technology stressors intersect with role conflict or unclear expectations, the risk of burnout rises and job satisfaction falls (Li, Seah &

Yuen, 2025). This pattern appears across sectors that rely on information work. It reflects a set of recurring mechanisms rather than isolated incidents.

The literature converges on a core set of technostress creators that define this field. They include overload from excessive digital demands, invasion through constant reachability, complexity due to the use of sophisticated tools, insecurity linked to skill obsolescence and uncertainty during continuous change. These dimensions offer a practical map for diagnosis and intervention. They also provide a stable foundation for measurement and testing, linking outcomes such as performance, engagement and health across the past three decades of research. In short, technostress dimensions frame how technology-related pressures emerge and why they persist in modern organisations (Rohwer *et al.*, 2022; Yener *et al.*, 2025; Li *et al.*, 2025). As a result, many researchers believe there should be more scholarly and theoretical studies on technostress in different contexts focusing on specific types of technologies and occupational roles (Li *et al.*, 2025; Yener *et al.*, 2025).

Studies conducted during the last two decades identified several sources of technostress (technostress creators). One prevalent issue was information overload, where individuals felt overwhelmed by the sheer volume of information received through computer systems (Al-Youzbaky, Hanna & Najeeb, 2022). Consequently, the introduction of new software or devices, along with the constant need for updates, required individuals to learn and adapt quickly, leading to feelings of role ambiguity and uncertainty (Boda, 2021).

Several factors contribute to the formation of technostress. Another pertinent reason for technostress is that employees are constantly exposed to information they cannot effectively manage (Yener, Arslan & Kiliç, 2021). The moderating role of technological self-efficacy in the relationship between technostress and employee performance helped reduce burnout. Some researchers highlight that humans have limited capabilities when it comes to dealing with information. This necessitates a negative relationship between ICT and humans, as ICT continues to evolve. Other researchers report that one of the significant stressors is employees' lack of control over the technology used in the workplace (Hsia, Chang & Tseng, 2014:53). Nobles (2022) adds that technological failures and technical glitches further exacerbate

individuals' stress levels, as they impede work performance and require troubleshooting.

Research on technostress has evolved from a predominantly individual-centric perspective to a broader, contextual lens (Palmucci, Giovando & Vincurova, 2025).. Recognising the role of context entails acknowledging that the effects of technostress are not uniform across individuals, organisations, cultures and societal contexts (Hwang, Kim & Rebman, 2022). Examining the contextual factors can yield a deeper understanding of the complex interplay between technology, individuals and their environment. Technostress is context dependent. Individuals and organisations need to recognise how setting, task demands and social norms shape both their form and their intensity. The same tool or workflow affects people differently across roles and institutions. These differences reflect the interaction between people and their environments during daily technology use (Hwang, Kim & Rebman, 2022). Stress research treats strain as specific to a situation. Distinct stressors and coping resources emerge under different conditions. Time pressure, connectivity expectations, data volume and support practices vary across contexts. Each of these shifts the appraisal of demands and the subsequent responses. Studies show that context reveals which stress-inducing conditions and strains matter most, and which situational variables need attention in analysis and intervention (Maier, Wirth, Laumer & Weitzel, 2015; Sarabadani, Carter & Compeau, 2018).

Method and practice should reflect this reality. Researchers should define the focal context, measure relevant environmental factors and test for subgroup differences across departments and roles. Managers should align rollouts with local workflows, provide role-specific training and set explicit norms for connectivity and response times. Treating technostress as context-specific improves explanation, strengthens external validity and guides actions that fit the setting under study (Hwang *et al.*, 2022; Maier *et al.*, 2017; Sarabadani *et al.*, 2018). The conditions, strains and situational variables that give rise to stress are based on the stress-inducing circumstances being examined, which inherently differ per environment. For example, stress-creating conditions could include stress arising from role allocation when stress is studied within an organisational context (Valta, Pflügner & Maier, 2021). Consequently, there have been appeals for ongoing theoretical and academic advancement within the

technostress domain, with a focus on exploring the technostress phenomenon within specific contexts involving distinct types of technologies, roles or tasks (Nastjuk *et al.*, 2024). Much research on the technostress phenomenon is written from a broad and general theoretical foundation for analysing the phenomenon, primarily focusing on various conditions that give rise to the formation of adverse effects leading to technostress. However, given that the use of information systems (IS) happens within a wide variety of working environments and contexts, not all individuals are affected by IS adoption in the same manner (Ioannou, Lycett & Marshan, 2022).

Singh, Bala, Lal Dey and Filieri (2022) conducted a quantitative study on the effects of work and the use of personal technology during the COVID-19 pandemic. The outcomes of their research revealed that both professional and personal digital platforms contributed to technostress during the mandated remote work period (Singh *et al.*, 2022). On the other hand, numerous scholars argue that stress could also be tied to societal factors. Societal and cultural norms, values and expectations influence individuals' perceptions of and responses to technology (Valta, Pflügner & Maier, 2021). Variations in cultural attitudes to technology, privacy concerns and societal expectations regarding availability and responsiveness can contribute to varying levels of technostress across different populations (Krishnan, 2017:157). Therefore, considering socio-cultural factors is crucial for understanding the diversity of technostress experiences.

The literature also suggests that technostress can be understood from a personal perspective. Personality traits, coping mechanisms and prior technology experiences contribute to an individual's susceptibility to technostress (Krishnan, 2017). Personal factors, such as technology literacy, self-efficacy and resilience, interact with the context to shape the individual's appraisal of and response to techno-stressors (Beare, O'Raghallaigh, McAvoy & Hayes, 2020). Exploring these personal, contextual factors enables a more comprehensive understanding of the individual's technostress experience. The occurrence of technostress in personal contexts is magnified by the omnipresence of technology, which creates new social challenges for employees as they find themselves constantly connected to social media and responding to emails, leading to negative feelings and burnout (Korzynski, Treacy & De Vries, 2016).

Technostress is also viewed as a managerial problem. This is because managers are tasked with managing the most crucial asset of any organisation: human resources. According to Hung *et al.* (2015), many organisations rely heavily on technology. This results in the digitisation of numerous business processes, which employees are then expected to cope with. The constant presence and rapid evolution of ICTs in the workplace have a tremendous impact on organisational processes (Ayyagari *et al.*, 2011). According to Wang *et al.* (2018), numerous studies conducted in Chinese organisations found that technostress levels of employees in these organisations were positively related to power centralisation and an organisational culture that encouraged innovation. However, it is essential to note that innovation was not seen as bad merely because of the existence of technostress. For instance, Tu *et al.* (2005) argue that although organisations have reported and acknowledged the formation of technostress due to IS adoption, productivity has not been impacted.

The positive aspect of stress is that not everyone responds to stressful situations in the same way. As a result, two concepts arise: techno-eustress and techno-distress. Tarafdar *et al.* (2019) define techno-eustress as positive stress that fosters job satisfaction, enhances vitality and does not contribute to imbalances, thereby facilitating decision-making in stressful situations. According to Tarafdar *et al.* (2019), techno-eustress emerges with new opportunities and challenges, allowing the development of new skills and norms. Accordingly, individuals who possess the skills to utilise these new technologies have a significant advantage in achieving their goals and overcoming difficulties, based on their interaction with and use of ICT. Adopting and utilising new technologies enables individuals to enhance their work performance and achieve greater efficiency. Other positive effects of technostress include improved individual performance, increased efficiency and enhanced personal well-being and stability. The positive impacts generated by technostress can be seen in operational-level employees who often use information systems under positive or motivating pressures (Wajcman & Rose, 2011). These positive pressures result in increased efficiency (such as reduced time and effort) and effectiveness, leading to better performance.

However, the literature notes that technostress can also pose long-term risks as individuals become overloaded with work, thereby leading to stress formation

(Salazar-Concha, 2021). Notwithstanding the positive effects on individual development alluded to earlier, the onset of stress can cause substantial harm to an individual. Scholars refer to this phenomenon (i.e., the adverse effects generated by people's use of ICT) as techno-distress. Tarafdar *et al.* (2019) argue that techno-distress emanates from the threats associated with ICT use. Since ICT adoption often exceeds an individual's competencies, it may be perceived as a threat rather than a benefit (Tarafdar *et al.*, 2019). The literature, therefore, makes it clear that although technostress was initially perceived as a disease, it came to be viewed as merely the inability of individuals to cope with the adoption of new technologies. Similarly, in support of this argument, Jena (2015) notes that it is natural for individuals to emphasise their preparedness and ability to cope with new technologies. Accordingly, organisations should introduce support mechanisms that would aid in reducing the occurrence of technostress among employees (Chen, 2015). This is also reflected in an academic setting, where academic staff are exposed to a range of technology-related stressors on a day-to-day basis. In higher education, many academics are often preoccupied with technostress management rather than teaching (Upadhyaya & Vrinda, 2021). This can result in a range of detrimental effects on academic staff performance (Khuzaini *et al.*, 2021), including decreased productivity, burnout and reduced job satisfaction (Li & Wang, 2021). The formation of technostress in the workplace is further influenced by ongoing changes in digital tools, which threaten job security and raise uncertainty for many employees. Therefore, it is crucial to address technostress challenges to achieve optimal work performance and to advance education and research within organisations (Bencsik & Csinger, 2021; Khuzaini *et al.*, 2021).

Higher education institutions have increasingly embraced technological advancements to enhance teaching and learning experiences. While technology integration holds great promise for improving educational outcomes, it also presents a range of challenges, particularly for academics at higher education institutions (Li & Wang, 2021). A challenge that has gained attention in recent years is technostress, a phenomenon arising from the prolonged use of technology, leading to stress and adverse psychological outcomes (Ayyagari *et al.*, 2011). Employees' stress and mental health represent essential concerns in the higher education industry (Arday, 2022). One might ask, "Why are academics prone to technostress?" University

academics are often stressed due to the constantly evolving nature of the technologies used in their work. Unfortunately, the higher education industry does not always consider the impact of these new technologies on the well-being of academics (Guoyan, Khaskheli, Raza, Khan & Hakim, 2021).

Moreover, this research holds broader implications for the future of education. As technology continues to evolve, the prevalence of technostress may increase if not addressed proactively (Li & Wang, 2021). Assessing the influence of technostress among university academics will enable researchers to develop practical recommendations to create a supportive technological ecosystem within higher education institutions (HEIs) (Chan & Fang, 2019).

Past research highlighted several factors contributing to the prevalence of technostress among academic staff members:

- The higher education sectors have seen a surge in the adoption of digital technologies to facilitate teaching and learning to boost productivity and increase graduation outputs (Almaiah et al., 2022).
- Due to this rapid adoption of digital technologies, academic staff are forced to keep up with the evolution of new technologies (Mohamed Hashim, Tlemsani & Matthews, 2022).
- The nature of academic work is multifaceted, encompassing research, teaching and administrative duties. Therefore, digital technologies may not be beneficial in all these areas (Mohamed Hashim, Tlemsani & Matthews, 2022).
- The advent of the COVID-19 pandemic resulted in many HEIs adopting technologies and online learning platforms, which have changed the workflow in the academic space (Deroncele-Acosta, Palacios-Núñez & Toribio-López, 2023).
- These shifts have resulted in academics having to keep up with rapid technological changes, which contributes to technostress.

Some scholars highlight the negative impact of workplace technologies on individuals' lives. In higher education, academic staff are expected to conduct online classes from home and be constantly connected to the information systems, which affects their daily lives (Wu, Wang, Mei & Liu, 2020). Therefore, many academic staff members may find

themselves always connected to information systems for pedagogical reasons, which increases the formation of technostress (Wu, Wang, Mei & Liu, 2020).

Zhang, Ding and Ma (2022) support this notion and further suggest that constant exposure to online platforms can lead to information overload, cognitive fatigue and feelings of being overwhelmed. There is a need for organisations to redesign work to mitigate the constant exposure to digital devices in the workplace (Arnold, Goldschmitt & Rigotti, 2023). If academics are not provided with proper support and guidance on managing this impact, it will lead to burnout and the development of technostress. However, it should be noted that providing training and support does not entirely mitigate the formation of technostress, as some academics are hesitant to adopt new technologies.

In the global context, technology integration has numerous benefits for university academics. Technology integration has transformed higher education, reshaping how university academics engage with their work. Embracing digital tools and technology offers numerous benefits for teaching, research and administrative efficiency. Among the many benefits cited by multiple studies is that technology enhances teaching and learning experiences. Technology offers a diverse range of educational tools, including learning management systems (LMS), multimedia resources and interactive platforms. These tools can facilitate personalised and interactive learning experiences, improving student engagement and academic performance (Hew & Cheung, 2014:47). Technology enables seamless collaboration among academics and students. Virtual communication tools, such as video conferencing and collaboration platforms, foster interdisciplinary research and facilitate remote collaboration (Kirkwood & Price, 2014:17; Mourtzis, Angelopoulos & Panopoulos, 2022:2). Hallal, Aloul, Alawnah, Kolli and Alnabulsi (2020:97), when highlighting the importance of technology in enhancing administrative efficiency, suggest that automation in education has become a significant factor and is directly related to the academic performance of students in universities. Technology streamlines administrative tasks, such as attendance tracking, course scheduling and grade management (Hallal *et al.*, 2020:98). This efficiency enables academics to allocate more time to teaching and research activities. Therefore, the benefits of using an automated toolset in academic learning may include increased efficiency, accuracy and convenience for both students and

university academics. Technology enables academics to access a vast repository of educational materials, including e-books, scholarly journals and online databases, providing them with a rich educational resource (Singh & Sharma, 2023:143).

### 2.2.3 Technostress dimensions and measuring instruments

Several instruments have been developed to measure technostress and its dimensions. Below is a summary of key instruments and their focus areas (see Table 2.1).

**Table 1.1: Summary of technostress measuring instruments**

| Instrument                            | Developers                          | Focus areas                                                                                      |
|---------------------------------------|-------------------------------------|--------------------------------------------------------------------------------------------------|
| Technostress Mitigation Model (TMM)   | Ayyagari, Grover, and Purvis (2019) | Organisational support, coping strategies and self-efficacy.                                     |
| Workplace Technostress Scale (WTS)    | Salanova <i>et al.</i> (2017)       | Emotional fatigue, job satisfaction, and their connection to technostress.                       |
| Extended Technostress Model (ETM)     | Maier, Laumer and Eckhardt (2019)   | Personal resources and organisational factors related to technostress.                           |
| Technostress Creators Inventory (TCI) | Tarafdar, Tu and Ragu-Nathan (2015) | Technostress creators include techno-overload, invasion, complexity, insecurity and uncertainty. |

The complexity of the technostress phenomenon necessitated the development of instruments to combat or mitigate the ill effects of technological stressors.

Ayyagari, Grover and Purvis (2019) developed the Technostress Mitigation Model (TMM) to help organisations and individuals mitigate technostress formation in the workplace. This model proposes different dimensions to reduce technostress; for example, coping strategies, self-efficacy and organisational support (Ayyagari, Grover & Purvis, 2019). However, despite its broad adoption, the TMM has been found to have limitations in its application. One such limitation is the sampling bias concerning work-related technostress. The Technostress Management Model offers a helpful starting point, yet its scope is narrow in context-specific assessment. It does not account for how technostress manifests across different settings, which limits its diagnostic value in applied studies (Borle *et al.*, 2021). It also does not explain causal

pathways. This weakens its use for evaluating technology-associated harm at work, where cause and effect matter for both theory and intervention.

Recent scholarship has called for refined instruments that keep pace with rapid digital change. In response, Maier, Laumer and Eckhardt (2019) proposed the Extended Technostress Model. The model integrates individual, technological and organisational factors, addressing gaps in earlier approaches that treated these dimensions in isolation (Aziz, 2021). Even so, essential constraints remain. Empirical work suggests that the model works best where socio-economic position shapes exposure and appraisal, which restricts its fit in settings where such variation is minimal – for example, among academics within the same institution (Wang, 2020; Borle, 2021). The model also places substantial weight on coping mechanisms during digital adoption. This emphasis narrows its value for studies that seek to map antecedents and outcomes beyond coping, as in the present study.

Salanova *et al.* (2017) developed the Workplace Technostress Scale to address persistent measurement problems. The scale targets key outcomes such as job satisfaction and mental fatigue, and it has seen validation and use in developing country contexts, where technostress poses distinct challenges (Chen, 2015). Yet the scale aligns more closely with older worker profiles and may over-sample higher socio-economic groups, which raises concerns about representativeness and external validity in diverse workforces (Borle, 2021). These issues point to the need for instruments that are sensitive to age, role, sector and socio-economic mix.

Over two decades, Tarafdar, Tu and Ragu-Nathan advanced the field with the Technostress Creators Inventory. The inventory operationalises four core stressors. Techno-invasion captures the spillover of work technology into personal time. Techno-overload reflects pressure to work faster and longer due to technology. Techno-complexity refers to the effort needed to learn and use digital tools. Techno-uncertainty captures strain from ongoing change in systems and features (Tarafdar, Tu & Ragu-Nathan, 2015). This structure clarifies sources of strain and supports hypothesis testing across roles and sectors.

Taken together, these models and measures show progress, but they also reveal persistent gaps. Some tools lack contextual sensitivity. Others prioritise coping over

causes and outcomes. Sampling issues recur. Future measurement models should integrate contextual moderators, test causal pathways and ensure inclusive sampling frames. Doing so will improve theoretical precision and support practical choices about prevention and intervention in technology-rich workplaces. According to Torres (2021), the TCI posits that these factors contribute to the formation of technostress in the workplace and should, therefore, be mitigated. The TCI argues that technostress arises due to the factors listed below:

- **Techno-overload** – refers to situations where employees are expected to work faster due to ICT usage.
- **Techno-invasion** – refers to situations wherein employees feel that their lives are invaded due to the constant use of ICT.
- **Techno-complexity** – describes situations wherein workers feel it is challenging to learn and use ICT.
- **Techno-insecurity** – refers to situations in which workers fear losing their jobs to other workers who are more capable of using ICT.
- **Techno-uncertainty** – describes situations wherein workers feel that ICTs are constantly changing or updated.

The TCI has been validated as effective in measuring technostress in various professional contexts, such as among Quebec lawyers (Cadieux, 2020). Recently, the TCI was used to assess teaching performance among educators (Vega-Muñoz & Estrada-Muñoz, 2020). Much like the WTS and ETS, the TCI also focuses on job satisfaction and employee well-being regarding the use of technology in the workplace (Kot, 2022). According to Jimmy (2023), the TCI helps assess how technological invasion causes stress among employees. Moreover, the TCI was employed to measure technostress in higher education during the COVID-19 pandemic (Boyer-Davis, 2022). The TCI does, however, have a few limitations. One of the limitations is that the TCI does not comprehensively assess technostress in the current landscape where technology adoption is rampant (Fischer, 2019). The Technostress Creators Inventory was first formulated in 2008, before today's digitally dense workplaces had fully emerged. Early versions reflected the technology environment of that period. Yet, subsequent work has adapted the inventory for contemporary settings in which new

organisational and individual factors shape technology adoption and strain (Tarafdar, Tu & Ragu-Nathan, 2008; Tarafdar, Tu & Ragu-Nathan, 2015).

This study employed the Technostress Creators Inventory to measure technostress in the target population. The choice was deliberate and linked to the study aims. The instrument offers a focused operationalisation of core stressors that align with the constructs under examination. Its structure supports precise measurement of exposure to technology-related demands and their appraisal, which fit the study's analytical objectives. Prior research have reported sound validity and reliability across workplace contexts, which supports confidence in the interpretability of scores in settings that resemble the present one (Tarafdar, Tu & Ragu-Nathan, 2015). Taken together, these features justified the use of the Technostress Creators Inventory as the preferred measure for this research.

### **2.3 TECHNOLOGICAL SELF-EFFICACY**

Technology self-efficacy supports how employees manage technostress at work (Yener, Arslan & Kiliç, 2021). It refers to individuals' belief in their capability to use digital tools and systems effectively in work tasks (Yener, Arslan & Kiliç, 2021). The construct builds on Bandura's theory of self-efficacy. People who hold strong beliefs about their capabilities exhibit more effective behaviours when they face work challenges (Bandura, 1997). Technology self-efficacy provides a lens to understand responses to stressors that arise from information systems in organisations (Ibrahim *et al.*, 2024). It shapes appraisal, emotion regulation and persistence when employees confront complex devices and software. It also supports adjustment during rapid technological change through greater confidence in learning, problem solving and recovery from setbacks (Caprara *et al.*, 2013). In empirical terms, higher technology self-efficacy aligns with better coping, lower strain and more stable performance under digital demands (Yener, Arslan & Kiliç, 2021; Ibrahim *et al.*, 2024). These features make technology self-efficacy a relevant personal resource in studies of technostress and work behaviour.

Institutions of higher learning face perplexing challenges when integrating educational technologies for teaching and learning (Cennamo, Ross & Ertmer, 2010; Clausen, 2007). For instance, Swart (2017) examined the role of technology in teaching

students to critically evaluate the credibility of sources in online learning environments. The conclusion was that the ability to use technology could assist teachers and students in developing critical thinking skills by providing access to diverse information sources and teaching them to assess reliability (Bloom & Doss, 2021; Swart, 2017:2). When dealing with successful and challenging situations, individuals leverage self-efficacy. Martin, Shaw and Daughenbaugh (2014) and Barton and Dexter (2020:90) argue that successful integration of educational technology in the classroom setting can aid in stimulating learning and student engagement (An & Reigeluth, 2011:57). However, this integration is reliant on the correct use of technology. Furthermore, utilising technology in the classroom offers a new approach to teaching and learning, which is ideal for both students and teachers (Swarts, 2017:1).

Incorporating technology into the curriculum helps students to learn better (An & Reigeluth, 2011:57). Online learning platforms provide an excellent opportunity for online discussions, further discussion platforms and diverse learning preferences to address various student needs (Swart, 2017:4). However, creating a technology-centred learning environment requires teachers to possess sound TSE beliefs. Creating a technology-enhanced student-centred learning environment ensures the personalisation and differentiation of the learning environment (An & Reigeluth, 2011:57).

However, it should be noted that this integration has not always resulted in improved learning efficiency. The literature highlights that educational technology necessitates a new curriculum, with unique teaching and learning strategies for educators and students (Swart, 2017:1). One of the challenges facing academics and teachers today is the lack of TSE beliefs. TSE is a significant component in understanding the frequency and success with which individuals use technology (Sure, 2009). Researchers have reported a long-standing link between TSE beliefs and academic achievement outcomes (Affuso *et al.*, 2017; Honicke & Broadbent, 2016; Travis *et al.*, 2020). Albee (2015) conducted a multiple case study investigating the relationship between TSE and online instructors. More specifically, the main aim of the research was to determine how online instructors with perceived high TSE beliefs used technology in their day-to-day online classes and how these instructors incorporated educational technology into best practices for online instruction. Albee (2015:119)

found that online instructors who believed in using technology effectively tended to adhere to established best practices when teaching online. In support of this notion, Alnoor, Al-Abrow, Abdullah and Abbas (2020:45) state that lecturers with higher TSE are more likely to adopt and effectively integrate technology into their teaching methods.

### **2.3.1 Theoretical foundations of technology self-efficacy**

Various theoretical frameworks have been used to understand the impact of TSE on the adoption and use of technology, particularly in educational settings. Some of these frameworks include the Social Cognitive Theory (SCT) by Albert Bandura (1977, 1998), the Technology Acceptance Model (TAM) by Davis (1989), the Unified Theory of Acceptance and Use of Technology (UTAUT) by Venkatesh *et al.* (2003), the Situated Learning Theory (SLT) by Lave and Wenger (1991) and Constructivism by Bada and Olusegun (2015).

TSE is a construct rooted in Bandura's (1977) Social Cognitive Theory, which defines self-efficacy as "intellectual activity by which one develops one's beliefs about one's ability to achieve a certain level of accomplishment". Bandura's Social Cognitive Theory positions self-efficacy at the centre of learning and adaptation (Bandura, 1998). Lecturers who trust their capability to master digital tools adopt those tools more readily for teaching. This conviction, termed technology self-efficacy, shapes how they plan lessons, solve problems and persist when technology fails (Yener *et al.*, 2021). Bandura argues that strong efficacy beliefs foster active engagement with challenges rather than passive acceptance of conditions. This insight underpins current work on technostress.

Researchers have extended Bandura's ideas through models of technology acceptance. Davis (1989) introduced the Technology Acceptance Model to explain why users embrace or reject new systems. The model rests on perceived ease of use and perceived usefulness. Recent studies apply the same framework to anxiety created by compulsory digital tools at work (Alshurafat *et al.*, 2023). Evidence shows that unfamiliar platforms provoke tension, especially in online learning environments where teachers and students must master new interfaces rapidly (Abuhassna *et al.*,

2023). Yet TAM omits variables linked to well-being. It predicts intention to use technology but leaves the emotional cost unexplored (Wang & Zhao, 2023).

The Unified Theory of Acceptance and Use of Technology offers a broader lens. Venkatesh (2003) combined multiple acceptance theories into one set of predictors: performance expectancy, effort expectancy, social influence and facilitating conditions. Studies in higher education and mobile commerce confirm its reach across cultures (Lim *et al.*, 2019; Imtiaz, 2018). Scholars now draw on UTAUT to map technostress during the implementation of new systems (Alshabeb, 2020). Even so, critics point to gaps in explaining strain outcomes and call for further theoretical development to address the demands of contemporary workplaces (Venkatesh, 2016; Ajibade, 2018).

Technology self-efficacy explains why lecturers engage with digital tools; taken together, TAM and UTAUT clarify when they adopt those tools. No single factor alone captures the full impact of mandatory technology on well-being. Integrating these perspectives can deepen understanding of technostress and guide support for educators facing rapid digital change. Regarding the explanation of TSE, Taiwo and Downe (2013) argue that the relationships between TSE and specific UTAUT constructs are weak, suggesting the need for further revision of the model.

According to Bandura's theory, self-efficacy is not a fixed trait but rather develops through past experiences, observations of others and feedback (Bandura, 1998). Educators' experiences with technology, both positive and negative, impact their self-efficacy beliefs regarding the use of technology for educational purposes. Measuring TSE is a valuable indicator of teachers' effectiveness when using instructional technology (Moore-Hayes, 2011). Against this backdrop, TSE is often regarded as one of the principal inhibitors of ICT adoption among educators (Kale & Goh, 2014:49). The lack of TSE among employees can have a profound impact on organisational performance. Alnoor *et al.* (2020:47) highlight that an optimal level of self-efficacy among employees is crucial for cultivating a positive view of the organisation's preparedness for change, particularly since the successful integration of new technology often demands a significant degree of TSE and competence. Low TSE and lack of digital skills appear to negatively influence teachers' meaningful pedagogical use of ICTs in schools (Kale & Goh, 2014; Ertmer & Ottenbreit-Leftwich, 2010; Cavas

*et al.*, 2009). Some scholars, such as Williams-Buffonge *et al.* (2021:9), argue that TSE could hinder technology adoption, contributing to poor performance. Overcoming this resistance and embracing technology can be challenging (Hani, Naz & Muhammad, 2021:94). Due to a lack of technology self-efficacy, some teachers may resist adopting technology in their teaching practices, fearing change or believing that traditional methods are more effective. This study, therefore, adopted the SCT as a theoretical lens to understand the moderating role of TSE in the relationship between technostress and IWP.

Social Cognitive Theory offers a strong basis for studying technostress because it centres on perceptions and beliefs, which shape how individuals experience digital demands at work (Shirish, 2021). Prior studies in information science show its value for explaining workplace information literacy and knowledge practices, reinforcing its relevance to technology-related behaviour (Middleton, 2019). The theory also clarifies the social mechanisms that frame stress responses, drawing attention to how norms, modelling and feedback within one's environment guide appraisal and action (Stana, 2021). Recent evidence in education supports this view. Perceptions and behaviours matter for understanding educators' confidence in using technology for teaching, and these beliefs influence uptake and persistence (Mert, 2023). Together, these insights position Social Cognitive Theory as an appropriate lens for testing the moderating role of technology self-efficacy in the link between technostress and work performance in higher education settings.

### **2.3.2 Outcomes of technology self-efficacy**

Technology shapes organisational processes and employee performance. Technology self-efficacy refers to individuals' belief in their ability to use digital tools to complete tasks and solve problems (Gomez Jr *et al.*, 2022). Strong technology self-efficacy aligns with higher job performance, more positive attitudes and fewer withdrawal behaviours (Rahman *et al.*, 2016). Organisations report better integration and use of digital systems when employees hold higher levels of technology self-efficacy (Bakar, Maat & Rosli, 2018). Evidence from the public sector shows the same pattern, with stronger beliefs predicting intention to use new systems (Xu, Khan & Shahzad, 2024). During the COVID-19 period, technology self-efficacy supported the move to electronic learning resources (Van, Quynh & Doanh, 2024). In education, high

computer self-efficacy remains a key enabler of technology-enhanced teaching and learning (Bakar, Maat & Rosli, 2018). Structural equation modelling conducted with Italian university students also showed that self-efficacy beliefs mediated the link between positivity and performance, influencing both in-role and extra-role behaviours (Barbaranelli *et al.*, 2019). Together, these findings position technology self-efficacy as a practical personal resource for digital work and learning.

Other researchers emphasise the significance of TSE in optimal work performance, suggesting that employees with high TSE demonstrate high work performance (Guha & Chakraborty, 2021; Saidy, Garanti & Sadaka, 2022; Kodden & Kodden, 2020; Kim, 2021). Moreover, it is evident from the literature that TSE plays a crucial role in workplaces where technology is an essential part of work. TSE is positively associated with job performance and organisational citizenship behaviour (Yang *et al.*, 2021) and negatively related to deviant workplace behaviour (Fida *et al.*, 2015).

Guha and Chakraborty (2021) examined the impact of TSE on work performance across various industries and confirmed that TSE did indeed moderate work performance. Self-efficacy moderated the link between technostress and job performance. Employees with stronger self-efficacy beliefs showed fewer performance losses under digital strain (Saidy *et al.*, 2022). Related work ties self-efficacy to well-being, work engagement and achievement, which are all relevant outcomes in technology-rich jobs (Kodden & Kodden, 2020). These findings align with Social Cognitive Theory – beliefs about capability shape behaviour and performance across tasks and contexts (Bandura, 2017).

In the Fourth Industrial Revolution organisations implement a wide range of technologies to improve productivity. Staff with high technology self-efficacy adopt and use these tools with greater confidence and speed, which supports strategic goals (Abun *et al.*, 2022). These employees also contribute to cultures of continuous learning and problem solving (Abun *et al.*, 2022). The same beliefs relate to higher job satisfaction and better well-being (Yang *et al.*, 2024). Evidence shows lower stress and higher satisfaction among workers who see themselves as competent in technology (Jena, 2015). These patterns support retention and stability (Abun *et al.*, 2022).

Benefits extend beyond the individual. Successful digital transformation needs leadership commitment and structured change management (Palad, 2022). Small and medium enterprises gain when their workforce blends technological skills with cognitive abilities suited to complex tasks (Roman & Rusu, 2022). In education, staff with high technology self-efficacy can reshape learning environments, which is a priority as institutions rely on educational technologies for sustainability and performance (Xu, Khan & Shahzad, 2024). Higher education systems also depend on these beliefs to strengthen operational effectiveness and workforce development (Bubou & Job, 2021). At the organisational level, strong technology self-efficacy positions firms to adopt new tools and realise gains in effectiveness (Alnoor *et al.*, 2020).

Taken together, the evidence shows a consistent pattern. Self-efficacy buffers technostress and supports performance. Technology self-efficacy advances adoption, learning, satisfaction and retention. Organisations that cultivate these beliefs improve the odds of successful and sustainable digital work.

### **2.3.3 TSE measuring instruments and dimensions**

Technology self-efficacy (TSE) remains a significant focus in organisational behaviour, especially in how it is conceptualised and measured. In technology-integrated educational settings, several studies have designed and validated survey instruments to assess TSE. These instruments include:

- The Technology Proficiency Self-Assessment (TPSA) survey (Ropp, 1999; Christensen & Knezek, 2017).
- Doğru's Scale (Doğru, 2017).
- Şendurur and Yildirim's Scale (Şendurur & Yildirim, 2019).
- Kavanoz, Yüksel and Özcan's Scale (Kavanoz, Yüksel & Özcan, 2015).
- Educator Technology Self-Efficacy Survey (ETS-ES) (Gentry *et al.*, 2014; Gentry, 2018).

The most notable instrument in measuring TSE in an educational context is the TPSA survey. Since its inception 20 years ago, the TPSA survey has maintained respectable psychometric properties for measuring self-efficacy skills for technology integration among educators in the classroom for teaching and learning purposes (Ropp, 1999).

Given the rapid changes in technology in recent years, Christensen and Knezek (2017) updated the TPSA survey scale. Meanwhile, Doğru (2017) and Şendurur and Yildirim (2019) developed their respective versions of scales to assess self-efficacy in technology usage and computer skills. However, the limitations of the latter two scales are that they tend to focus on perceptions of self-efficacy regarding technology use within the context of basic skills and anxiety states (Doğru, 2017; Şendurur & Yildirim, 2019).

It bears pointing out that the TPSA does have some challenges in assessing TSE. A notable challenge is that it focuses solely on pre-service teachers, with a relatively small sample. Moreover, the instrument may not fully capture the range of technology capabilities needed for 21st-century teaching, as it primarily covers self-perceived proficiency rather than actual skills (Jamieson-Proctor, Finger & Albion, 2010). Additionally, the TPSA does not address cultural and contextual factors, such as differences in access to technology and ethnicity. The TPSA survey is appropriate, but it should be paired with other measures to more fully assess educators' technology proficiency. The development of self-efficacy scales for educators has received sustained research attention. Gentry *et al.* (2014) created the ETS-ES to gauge teachers' self-efficacy in modelling twenty-first-century skills, using the International Society for Technology in Education standards as a benchmark. This alignment is behaviour-centred and targets skills that matter in contemporary classrooms (Gentry *et al.*, 2014; Simsek & Yazar, 2016).

Evidence supports the ETS-ES as a reliable and valid instrument. Validation work reports strong internal consistency and construct validity (Gentry, 2018). The instrument responds to the need for a comprehensive measure of educators' technology self-efficacy and draws on self-efficacy theory. It captures beliefs about the effective use of technology tools across instructional contexts. Its dimensions include technological, pedagogical and knowledge-based aspects, as well as perceived ease of use and instructional integration (Gentry, 2018).

This multidimensional structure is a core strength. Technological pedagogical knowledge assesses educators' confidence in integrating technology into pedagogical practices. Studies recommend multi-dimensional scales for self-efficacy in education and technology standards work, reinforcing the ETS-ES approach (Malandrakis *et al.*,

2018; Simsek & Yazar, 2016). Scholars also argue for comprehensive measurement of teachers' self-efficacy and highlight the value of multidimensionality for understanding teacher engagement, which the ETS-ES provides (Shertzer, 2023; Holden, 2021). On this basis, the present study adopted the ETS-ES because of its documented reliability and validity and the breadth of its constructs, which support assessment of educators' evolving needs in the digital age.

## **2.4 PROACTIVE PERSONALITY**

Proactive personality has its roots in business management and economics. It describes a stable disposition characterised by the tendency to initiate change in one's environment (Bateman & Crant, 1993). Scholars treat it as a form of personal initiative that supports productivity at work (Din *et al.*, 2023). It is also the most examined proactivity construct in organisational behaviour (Crant, Hu & Jiang, 2016). Individuals with proactive traits tend to fit their organisations and job roles well (Weng, Rasheed & Yue, 2020). They often show openness to experience and conscientiousness, which can raise job performance (Alikaj, Ning & Wu, 2021). Proactive individuals act as initiators, which supports organisational success (Maziriri, Nyagadza & Chuchu, 2023). The spread of digital technologies in the workplace has increased demand for such a mindset, as it helps employees meet technology requirements effectively. The higher education sector is not immune to this practice. Institutions of higher education are seeking to ensure that they employ and retain employees with strong proactive personalities (Zhang, Li & Gamble, 2022). Academic staff members in higher education are expected to possess an optimal proactive personality to cope with the technological demands in their workplace.

### **2.4.1 Theoretical foundations of proactive personality**

The concept of proactive personality stems from the fields of personality psychology and organisational behaviour, which have sought to untangle the complexities of human behaviour and its consistency across various situations. Early personality theories, such as those by Kurt Lewin (1947) and Victor Vroom (1964), laid the groundwork for the concept of proactivity. Vroom's expectancy theory posited that individuals are motivated to act proactively when they expect their efforts to yield desirable outcomes (Vroom, 1964), whilst Lewin (1947) highlighted the role of

proactive forces in driving behaviour by comparing driving and restraining forces within individuals. These early conceptualisations emphasised the role of individual differences in shaping human behaviour. However, the limitation of the early theories was that they did not provide a solid foundation for understanding personality. As a result, other theories have subsequently been developed to address these limitations; for example, the Goal-Setting Theory (Locke & Latham, 2002), Positive Psychology (Seligman, 1999), Evolutionary Psychology (Duntley & Buss, 2008) and Proactive Personality Theory (Bateman & Crant, 1993).

One theoretical framework that sheds light on the underlying mechanisms of proactive personality is Goal Theory, also known as the goal-setting theory. The goal-setting theory originates from social-cognitive psychology, which posits that individuals are driven by a set of cognitive representations of desired outcomes, commonly referred to as goals. In essence, goal theory is the seminal work of Locke and Latham (2002) about goal-setting, emphasising the importance of setting unambiguous and challenging goals to enhance motivation and performance. According to Maehr (2001), goal theory has been developed over the past three decades to address the importance of purpose and to explore the quality of actions taken by an individual. Goal theory offers a central perspective on achievement in education (Maehr, 2001). A goal refers to a targeted outcome that guides behaviour across contexts (Locke, 1991). Goal-setting theory states that specific and challenging goals improve performance (Locke & Latham, 2015). Research tests the roles of goal commitment, goal difficulty, goal origin, self-efficacy, individual differences, job satisfaction and feedback, and links these factors to performance outcomes (Gkizani & Galanakis, 2022). Proactive personality aligns with positive teamwork outcomes (Asahiah *et al.*, 2024). It relates to learning goal orientation and to proactive achievement of goals, which indicate a tendency to set and pursue challenging targets (Odoardi, 2015). Evidence connects a proactive personality with career success and life satisfaction, both of which are associated with goal attainment (Wang & Lei, 2023).

Proactive individuals take initiative and persist in pursuing goals. Goal setting functions as a self-regulatory process, also for people with present-bias preferences (Zhou, 2021). Work extending goal theory shows that proactive goal management strengthens the links between motivational states, self-efficacy and job performance

(Wang *et al.*, 2022). Work design shapes proactivity. Job demands and job control influence proactive personality, and high job autonomy strengthens its link with performance (Li *et al.*, 2014; Wang & Lei, 2023). Proactive behaviour also signals competence. Observers often rate proactive employees as socially superior and more capable (Huang *et al.*, 2022).

Foundational contributions can be traced to Bateman and Crant. The Proactive Personality Scale measures differences in the tendency to take action to change one's environment (Bateman & Crant, 1995; Kaya, 2024). Proactive behaviour contributes to work performance because it enables the quick completion of work-related tasks.

McCormick *et al.* (2019) characterise the archetypal "proactive personality" as an individual who demonstrates relative freedom from the influence of situational factors and actively instigates changes in his or her environment. Chen *et al.* (2021) suggest that the PPS may have implications for work performance and technostress (Tiwari, 2021). Given the definition of proactive personality and previous research on the correlates of technostress, this study adopted the proactive scale developed by Crant (1995).

#### **2.4.2 Outcomes of a proactive personality**

Proactivity encompasses a set of behaviours geared towards initiating and driving changes within oneself or one's surroundings (Parker & Bindl, 2017:1192). Proactive individuals have the ability to recognise and capitalise on opportunities, displaying a strong sense of initiative and determination in effecting significant changes (Arain, Hameed & Crawshaw, 2019:556). In contrast, those lacking a proactive personality exhibit contrasting behaviour, often failing to identify opportunities or initiate change. According to Parker and Collins (2019:634), various facets of proactive behaviour and their implications play a significant role in an individual's personality and initiative. In support of this, Seibert and Kraemer (2018:1) argue that proactive behaviour is linked to career success and enhances one's career path. Crant (1996:3) emphasises that proactivity should not be confused with affective traits—such as well-being—and cognitive traits, like locus of control. In essence, proactivity is rooted in the ability to initiate and uphold actions that directly affect the surrounding environment in which individuals find themselves (Bateman & Crant, 1993). Other scholars, such as

Bandura (1977) and Schneider (1983), argue that proactivity involves individuals' ability to shape their environment. In this context, Bandura (1977) posits that a reciprocal relationship exists between the individual, the environment and behaviour. A plethora of research considers employee proactivity related to organisational outcomes and individual groups (Belwalkar & Tobacyk, 2017:529; Crant, 1996; Parker & Bindl, 2017; Crant, Hu & Jiang, 2016).

Proactivity plays a vital role in how employees self-initiate change, which, in turn, could enhance employee productivity and organisational outcomes. According to Vaugh, Bindl and Parker (2017:1192), proactive work behaviour is viewed as a process through which employees identify potential challenges and opportunities in their work environment and self-initiate changes to their environment and work processes. However, it is essential to note that employees do not exist in a vacuum, unaffected by other factors in their surrounding environment. Their proactivity could also be hampered by the work of others within the organisation.

#### **2.4.3 Proactive personality measuring instruments and dimensions**

Research consistently demonstrates the significant impact of a proactive personality on various aspects of organisational behaviour. Spitzmuller *et al.* (2015) highlight the unique and positive influence of proactive personality on job satisfaction, organisational citizenship behaviour and overall job performance. Johari *et al.* (2022) further emphasise the importance of proactive personality in enhancing job performance, particularly when employees have high job autonomy. Wang (2017) extends this by showing that proactive personality is related to performance through its relationship with engagement and that this relationship can be moderated by other factors such as perceived organisational support and team proactive personality composition. Proactive behaviour is crucial for individual and organisational success (Abdul Hamid, 2022). Proactive individuals shape work contexts that support effective job performance (Johari *et al.*, 2022). The Proactive Personality Scale has proved to be the most comprehensive instrument for assessing proactivity in recent decades. Developed by Bateman and Crant, it measures individual differences in the inclination to act and to change one's environment (Bateman & Crant, 1993; Bateman & Crant, 1995). The initial studies drew on three university student samples and yielded a 17-item scale (Bateman & Crant, 1993). Evidence supports its criterion validity and its

incremental validity beyond the Big Five in predicting job performance (Crant, 1995). Further validation work shows that the scale is distinct from other individual difference constructs and predicts organisational citizenship behaviours (Trifiletti *et al.*, 2009).

## **2.5 INDIVIDUAL WORK PERFORMANCE**

Individual work performance receives sustained attention in organisational and occupational psychology because it shapes employee well-being, productivity and organisational success (Bedarkar & Pandita, 2014). The growth of digital work increases its relevance, especially when examining links with technostress. Scholars identify rigorous assessment of IWP among employees, including middle managers, as a priority research area (Ramos-Villagrasa *et al.*, 2019).

Foundational definitions frame IWP as behaviours or actions aligned with organisational goals (Campbell, 1990). Related work defines IWP as “any behaviours or activities which affect the goals of the organisation itself” (Koopmans *et al.*, 2011). In practice, IWP refers to the observable behaviours, actions and outcomes displayed in the workplace. It is no surprise that scholars argue that IWP is the “ultimate dependent variable” in people management, rendering its assessment a critical issue (Ramos-Villagrasa *et al.*, 2019). In support of this, Campbell and Wiernik (2015) note that the role of work performance among individuals drives organisations and, ultimately, the economy. In this study, IWP is defined in terms of behaviours or actions of employees that occur within an organisation rather than focusing on the results of these actions (Koopmans *et al.*, 2011). Considering this definition, Platania *et al.* (2023) postulate that the IWP construct consists of behaviours under the control of the individual, excluding those constrained by the environment.

### **2.5.1 Theoretical foundations of individual work performance**

Various theories serve as the theoretical underpinning of IWP, such as the Goal-Setting Theory (Locke & Latham, 1991), Expectancy Theory (Vroom, 1964), Ability-Motivation-Opportunity (AMO) framework (MacInnis & Jaworski, 1989; Hughes, 2007), Job Characteristics Model (Hackman & Oldham, 1976), Social Cognitive Theory (Bandura, 2008) and Koopmans IWP Conceptual Framework (Koopmans *et al.*, 2011). Theories that guide the conceptualisation of individual work performance draw on organisational psychology and management. Goal-Setting Theory proposes that

specific and challenging goals motivate people to improve performance (Locke & Latham, 1991). Expectancy Theory suggests that people act when they anticipate valued outcomes, linking effort, performance and rewards (Vroom, 1964). These ideas frame the study of work motivation and behaviour. IWP was not widely recognised until the early 1980s (Campbell & Wiernik, 2015). A systematic review mapped a framework for measuring IWP across settings (Koopmans *et al.*, 2011).

The Ability Motivation Opportunity framework explains drivers of IWP. The original model viewed performance as a function of ability, motivation and opportunity (MacInnis & Jaworski, 1989). A revised version has been applied in information systems and human resource management (Hughes, 2007). In information systems, ability and opportunity moderate the link between motivation and behaviour (Hughes, 2007). In human resource management, the model informs High Performance Work Systems and relates to practices and outcomes (Obaid, Ahmad & Mumtaz, 2022).

Scholars report challenges in defining and measuring AMO variables and in tracing their interactions and processes (Bos Nehles *et al.*, 2023). Studies link AMO to IWP at system and individual levels (Edgar, Zhang & Blaker, 2021; Tuuli & Van Rhee, 2021). Teamwork and organisational context align with AMO predictions for performance outcomes (Mahdy & Alhadi, 2021). Critics note weak construct definition and testing and uneven adaptation across human resource studies (Kellner, Cafferkey & Townsend, 2019), with continuing calls for precise constructs, clear measures and stronger empirical tests that address the complexity among AMO components (Bos Nehles *et al.*, 2023).

The Job Characteristics Model links job design to work outcomes. It identifies five core features, namely, skill variety, task identity, task significance, autonomy and feedback (Hackman & Oldham, 1976). These features shape employee behaviour and performance (Hackman & Oldham, 1976). Evidence supports the role of task variety, autonomy and feedback in strengthening motivation and performance (DeVaro & Brookshire, 2007; Fried & Ferris, 1987; Kamani, 2020).

Research connects the Job Characteristics Model to IWP. Findings generally support positive links between job features and performance, while also calling for more work where results diverge (Matilu & K'Obonyo, 2018). Scholars have tested moderators.

Growth needs, coworker satisfaction and supervisory satisfaction influence the link between job characteristics and internal motivation (Oldham, 1976; Sims & Szilagyi, 1976). Self-actualisation requires strength and also moderates effects in job enrichment (Gould, 2024). Competency, effort and direction of behaviour influence performance and moderate the ability to perform (Sabuhari *et al.*, 2020). Measurement choices vary and matter for personnel selection (Le Sante, Eaton & Viswesvaran, 2021).

Motivation theory has long informed explanations of behaviour. Expectancy Theory organises evidence in vocational psychology and motivation (Vroom, 1964). Studies apply it to decision support systems, work effectiveness and achievement in education (De Sanctis, 1983; Hackman, 1968; Wigfield, 2010). Some studies report strong support for the theory, while other studies report moderate support (Mitchell & Albright, 1972; Wigfield & Cambria, 2010). The theory states that behaviour reflects the instrumentality of an act for desired outcomes, combined with the value placed on those outcomes (Mitchell & Albright, 1972).

Expectancy Theory has two parts. Valence refers to affective orientation to outcomes (Vroom, 1964). An outcome is positively valent when a person prefers attaining it, zero when the person is indifferent and negative when the person prefers not to attain it (Vroom, 1964). Expectancy refers to a belief about the likelihood that an act will lead to an outcome, ranging from zero to one (Vroom, 1964). Expectancy reflects the judged probability that effort will produce successful performance (Vroom, 1964).

Empirical tests linked Expectancy Theory to work effectiveness in a study of telephone service representatives. Expectancy variables were related to job involvement and effort, supervisor appraisals and error and sales data (Hackman & Porter, 1968). Expectancy Theory predicts work effectiveness, work motivation, effort and job performance (Hackman & Porter, 1968; Supatn & Puapradit, 2019). Expectancy, which links effort to performance, appears central to IWP. Evidence for the role of valence is mixed across studies (Supatn & Puapradit, 2019).

Social Cognitive Theory also relates to IWP. Self-efficacy predicts computer performance at work (Harrison *et al.*, 1997). Self-efficacy and performance goals predict work performance in broader settings (Brown & O'Donnell, 2011). Group

processes matter. Stronger group identification can raise individual productivity in groups (Worchel, 1998). Work design and social context shape reactions to performance evaluation, with resource adequacy, communication, coworker relations and preparation time playing key roles (Klemm Verbos, Miller & Goswami, 2014).

The literature suggests that IWP is a crucial and relevant outcome measure in contemporary occupational health and safety studies. Many researchers in various fields, such as health, education, management and industrial psychology, have been attempting to discover the predictors of IWP (Koopmans *et al.*, 2012). IWP was initially defined by Campbell (1990) as “behaviours or actions that are relevant to the organisation's goals”. Rotundo and Sackett (2002) highlight that the IWP construct predominantly focuses on the behaviours or actions of the employee rather than the consequences of those actions. It is, therefore, crucial to understand the theoretical foundations of IWP. As such, this study adopted the IWP conceptual framework proposed and validated by Koopmans *et al.* (2011). Koopmans *et al.* (2011:856) argue that IWP has been conceptualised differently in various fields due to its importance. Accordingly, IWP is a construct relevant to fields such as management, occupational health and organisational psychology (Koopmans *et al.*, 2011:856).

Individual work performance is a second-order formative construct composed of three first-order reflective dimensions, namely, contextual performance, task performance and counterproductive work behaviour (Koopmans *et al.*, 2014). Koopmans’s model accentuates the role of context, including organisational culture, leadership style and resource availability, in shaping performance capacity (Koopmans *et al.*, 2011:857). A supportive environment with clear communication, adequate resources and autonomy contributes to higher performance levels (Koopmans *et al.*, 2011:856). The model also stresses fit between an employee’s skills, knowledge, motivation and assigned tasks, which raises job satisfaction and strengthens performance outcomes (Koopmans *et al.*, 2011). Scholars note the dynamic interplay between individual capabilities and the work context in explaining performance (Ravesangar, Muthuveloo & Ping, 2018).

As a second-order formative construct, individual work performance is not directly observable or measurable. Researchers infer it from its first-order indicators of contextual performance, task performance and counterproductive work behaviour. It is a higher-level concept that combines these three underlying dimensions. According

to Koopmans *et al.* (2011), the term "second-order" indicates that IWP is a higher-level construct that comprises the three first-order constructs. It's an overarching concept that is not directly observed but is inferred from the observed behaviours and characteristics of employees in these three dimensions: CP, TP and CWB. CP, a first-order reflective construct, refers to the extra-role or discretionary behaviours an employee engages in beyond formal job requirements (Koopmans, 2011:861). CP could include helping colleagues, volunteering for additional tasks or taking part in organisational initiatives (Conway, 1999:4). Essentially, this dimension reflects an employee's willingness to contribute positively to the broader work environment.

In organisational psychology, TP is regarded as a first-order reflective construct and a crucial dimension of IWP. Campbell (1990) defines TP as "the proficiency with which one performs central job tasks". Task performance encompasses the core job duties and responsibilities of an employee and includes the specific tasks, duties and responsibilities outlined in an employee's job description (Carlos & Rodrigues, 2016). This dimension assesses how well employees perform their primary job functions.

The third and last first-order reflective construct, according to Koopmans *et al.* (2011), is counterproductive work behaviour (CWB). CWB encompasses actions or behaviours that are detrimental to the organisation (Fox *et al.*, 2012), such as absenteeism, workplace deviance, theft or any behaviour that harms the organisation or its members. CWB is regarded as a first-order reflective construct, as it is defined by its indicators and is presumed to cause variations in the construct.

These three first-order constructs (CP, TP and CWB) interact to shape an individual's overall work performance (i.e., IWP) (Motowidlo, Borman & Schmit, 2014). Notably, high levels of CP and TP are generally regarded as positive contributors to overall IWP, whereas CWB is considered a negative contributor (Debusscher, Hofmans & De Fruyt, 2016:303). Furthermore, researchers and organisations have in the past used various tools and assessments to measure and evaluate each of these constructs separately and, by extension, the second-order construct of IWP. Understanding the multidimensional nature of IWP can have practical implications for employee selection, training and performance management (Van der Vaart, 2021:2). In addition, it highlights the importance of not only focusing on task performance but also on

fostering positive contextual behaviours and mitigating counterproductive work behaviours (Van der Vaart, 2021:2).

### **2.5.2 Outcomes of individual work performance**

IWP is a crucial component of organisational success, with both behavioural, individual characteristics and outcome components (Sonnentag, Volmer & Spsychala, 2008). Work characteristics and individual dispositions shape job performance. Work characteristics influence performance indirectly through employees' perceptions of their importance (Peiró *et al.*, 2020; Esthi, 2020). Job performance, as a behavioural outcome, reflects positive attitudes toward the organisation (Ramawickrama *et al.*, 2017). High performance promotes personal satisfaction and career advancement, and it benefits the organisation (Widarko & Anwarodin, 2022). Organisations seek to attract and retain high performers (Lee, Werner & Kim, 2016).

Research shows an interplay between individual and contextual factors and employee performance. Work engagement, motivation and stable traits have a significant influence on performance (Riyanto, Endri & Herlisha, 2021). Performance reflects both individual and organisational factors acting together (Esthi, 2020). High individual performance not only benefits the individual in terms of satisfaction and career opportunities but also contributes to organisational success (Henttonen, Kianto & Ritala, 2016).

However, it should be noted that organisational factors equally influence work performance in the workplace. Factors such as work-life balance and personality have been found to impact individual job performance significantly (Boon *et al.*, 2012). A review and meta-analysis of literature by Akpa, Asikhia and Nneji (2021) found that organisational culture was shaped by numerous factors, which in turn influenced the work performance of employees. Organisations use a range of tools to build a positive climate that supports high work performance (Akpa *et al.*, 2021). Work attitudes, especially job satisfaction and organisational commitment, relate positively to perceived performance at both individual and organisational levels (Salminen *et al.*, 2017). Knowledge sharing shapes individual work performance, which then influences organisational results (Henttonen *et al.*, 2016).

Employee engagement is used to motivate staff, raise job satisfaction and strengthen competitive advantage (Riyanto *et al.*, 2021). Its effect on performance is often mediated by motivation and job satisfaction (Riyanto *et al.*, 2021). Performance appraisal feedback helps employees develop skills, realise their potential and improve work performance (Susanto *et al.*, 2020). Perceived organisational support fosters a stronger sense of responsibility to the organisation, which promotes effort and contribution to organisational goals (Silitonga *et al.*, 2020).

The COVID-19 period increased reliance on technology in daily operations. In this context, technology self-efficacy had a significant effect on individual work performance, with Industry 4.0 technologies moderating performance links that supported organisational outcomes (Narayanamurthy & Tortorella, 2021). Collectively, studies show the central role of individual work performance in shaping organisational performance.

### **2.5.3 Individual work performance measuring instruments and dimensions**

In 2000, Brewer and Selden developed a model to elucidate organisational performance. This model identifies two key components that define the concept: firstly, factors linked to the organisation itself, and secondly, individual-oriented factors. These individual factors encompass various elements, notably individual performance. Additionally, Brewer and Selden (2000:688) highlight that the most influential variables in organisational performance are those necessitating increased employee engagement. Considering this, Carlos and Rodrigues (2016:280) mention that measuring and analysing individual performance are paramount to understanding organisational performance.

Many scholars argue that measuring IWP requires reliable and valid assessment tools. Accurate measurement is crucial for studying IWP effectively. Traditional methods include supervisor assessments, self-reports and peer evaluations (Kennerley & Neely, 2002; Williams & Anderson, 2017). More recent approaches and methodologies for measuring IWP include quantifiable measurements, such as sales statistics, project accomplishment rates and error frequency (Williams & Anderson, 2017). When measuring performance it is crucial to align the choice of measurement to the specific context under investigation. The literature indicates that IWP

encompasses various dimensions, such as task performance (i.e., the execution of core job duties), contextual performance (i.e., citizenship behaviours that contribute to the organisational climate) and adaptive performance (ability to adjust to changing circumstances and challenges) (Odongo, Wang, Suntu & Bishoge, 2019). Each dimension of work performance provides unique insights into an employee's effectiveness and contribution to organisational objectives (Pradhan & Jena, 2017:70).

The evaluation of IWP has been acknowledged for a considerable time as a notable hurdle encountered by managers and researchers (Murphy, 2008). Generally, approaches employed to assess IWP can be categorised into two main groups: (1) measurements using organisational records and (2) subjective evaluations. The latter involves criterion-referenced judgments, wherein individuals' evaluations are conducted without comparing them to others (e.g., ratings), or norm-referenced judgments, which include evaluating individuals by comparing them to their peers (e.g., rankings). In the early 2000s, the measurement of IWP primarily focused on objective measures of productivity (for example, counting specified completed actions, output reached within an organisation or the number of days absent from work) (Koopmans *et al.*, 2011). Numerous authors critiqued the subjective evaluations of IWP, questioning who had the authority to measure employees' IWP. Murphy (2008) notes that these measurements were considered inadequate and lacked uniform standards. Against this backdrop, this research employed the objective measurement developed by Koopmans *et al.* (2011).

## **2.6 RELATIONSHIP BETWEEN TECHNOSTRESS AND INDIVIDUAL WORK PERFORMANCE**

In the contemporary landscape, the pervasive integration of technology in work environments has yielded transformative benefits alongside emerging challenges like technostress, which is a multifaceted phenomenon with profound implications for IWP. As such, exploring the intricate relationship between technostress and work performance, as well as its overarching impact on employee productivity, is imperative.

Studying the relationship between IWP and technostress provides insights into how technostress influences work performance and how reduced performance may lead to higher levels of technostress (Marchiori, Mainardes & Rodrigues, 2019:2). Moreover, this line of research can uncover potential coping mechanisms and interventions to mitigate the adverse effects of technostress on work performance.

Many studies have found that low levels of experienced stress are associated with better performance on complex tasks (McGrath, 1976; Mandrick, Peysakhovich, Rémy, Lepron & Causse, 2016). When individuals experience stressors while performing their jobs, it increases the likelihood of accidents and mistakes in specific tasks (Kahn & Byosiére, 1992; Bridger, Brasher & Day, 2012). In addition, trade studies in technostress suggest that it hampers performance in each job role and results in computer-use-related mistakes, such as incorrect data entry (Tarafdar, Pullins & Ragu-Nathan, 2015). Technostress creators (TSCs) have been associated with a decreasing ability to utilise information systems (IS) to improve work (Tarafdar *et al.*, 2010). From this limited investigation into the performance impacts of technostress, it is clear that TSC can have potentially adverse effects on the overall execution of the role and on performance related to the individual's use of IS for accomplishing tasks. Viewed from both theoretical and practical perspectives, effective performance management favours employees' performance and overall organisational efficiency. This influence is contingent upon understanding their responsibilities and providing constructive feedback on their ongoing duties (Cesário, Rodrigues, Castanheira & Sabino, 2022:131).

The surge in digital communication tools and platforms can provoke cognitive disruptions that significantly undermine efficient work performance. Constant notifications and information overload fragment attention spans and reduce focus (Kaminske, Brown, Aylward & Haller, 2022:1490). It is argued that this stimulus overload culminates in cognitive strain, hindering the timely and accurate processing of information (Tarafdar *et al.*, 2020). Complex tasks that necessitate deep cognitive engagement become susceptible to errors and suboptimal outcomes in the presence of technostress. The interface between technostress and emotional well-being is pivotal in its influence on work performance. The dissolution of boundaries between work and personal life, facilitated by continuous connectivity, leads to emotional

exhaustion. For instance, in a study among Chilean teachers at primary and secondary schools, Estrada-Muñoz, Castillo, Vega-Muñoz and Boada-Grau (2020:2) found that 12% of the participating Chilean teachers felt techno-fatigued, and 13% felt techno-anxious. The incessant pressure to remain digitally responsive fuels anxiety and impedes stress management (Estrada-Muñoz *et al.*, 2020:7). This phenomenon creates burnout and emotional stress, resulting in low work performance.

Technostress reduces work productivity. Cognitive strain and emotional burden reduce task performance and lengthen completion times (Derks *et al.*, 2016). Reduced efficiency manifests as absenteeism and presenteeism, which produce suboptimal performance even when employees are at work (Ioannou & Papazafeiropoulou, 2017:1). Together, these effects lower overall productivity and lead to substantial revenue loss for organisations.

## **2.7 EMPIRICAL RESEARCH ON LEVELS, GENDER AND AGE DIFFERENCES IN TECHNOSTRESS, INDIVIDUAL WORK PERFORMANCE, TECHNOLOGY SELF-EFFICACY AND PROACTIVE PERSONALITY**

This section reports empirical findings on technostress, individual work performance, technology self-efficacy and proactive personality. It examines mean scores and differences by gender and age. It also analyses the relationships between technostress, work performance and demographic factors.

Research on technostress among professionals has found moderate levels of stress induced by information and communication technologies. Health professionals in Swiss psychiatric hospitals reported moderate technostress scores, with a mean of 39.06 out of 100 (Golz *et al.*, 2021). Notably, physicians and nurses experienced higher technostress than other professions (Golz *et al.*, 2021). In the education sector, government secondary school teachers in Kerala showed an approximately normal distribution of technostress scores (IS Technostress *et al.*, 2022). Academic staff in distance education institutions manifested significantly higher levels of technostress than administrative staff (Agbu & Simeon, 2011). Chen's (2015) study on technostress, measured across five dimensions—techno-overload, techno-invasion, techno-complexity, techno-insecurity and techno-uncertainty—found an overall mean score of  $M = 2.95$ ,  $SD = 0.57$ , indicating a moderate level of perceived technostress among

respondents. The highest-rated stressors were techno-uncertainty ( $M = 3.29$ ,  $SD = 0.82$ ) and techno-overload ( $M = 3.24$ ,  $SD = 0.80$ ), indicating that uncertainty about technology and workload pressures resulting from technology were primary concerns. This finding highlights the importance of addressing technostress in the workplace, a pressing issue that cannot be ignored. In contrast, techno-insecurity had the lowest mean score ( $M = 2.36$ ,  $SD = 0.80$ ), implying that respondents were relatively less concerned about job security due to technological advancements (Chen, 2015).

Arslan *et al.* (2022) reported a significant rise in mean technostress scores after the onset of COVID-19, indicating that the shift to digital teaching increased strain on educators. Gender differences were not significant. Male and female teachers showed similar levels before and after the outbreak (Arslan *et al.*, 2022).

Arslan and Şahin (2024) found moderate technostress among academic staff. Levels differed by gender, seniority, teaching specialisation, educational status and school type. Technostress correlated negatively with problem-solving skills, reducing teachers' effectiveness in addressing problems (Arslan & Şahin, 2024).

Aktan and Toraman (2022) examined 525 teachers engaged in distance education. Intensive technology use increased technostress, harming personal life and job performance. Higher workload and demands for technological adaptability contributed to the increase. Technostress varied by gender and institution. Private school teachers reported higher levels than public school teachers (Aktan & Toraman, 2022).

Mokh *et al.* (2021) studied Palestinian English language teachers. Technostress did not differ by gender, length of service, educational level or frequency of internet use. Technology-related factors were the primary sources of strain (Mokhtari *et al.*, 2021).

Estrada-Muñoz *et al.* (2020) reported a notable prevalence of technostress among Chilean teachers. Techno-fatigue affected 12 percent, while techno-anxiety affected 13 percent. Eleven percent experienced both conditions. Male teachers reported higher techno-anxiety and techno-fatigue than female teachers (Estrada-Muñoz *et al.*, 2020).

Koopmans *et al.* (2014) assessed the Individual Work Performance Questionnaire across three dimensions. Task performance had  $M = 2.71$ ,  $SD = 0.66$ . Contextual performance had  $M = 2.31$ ,  $SD = 0.77$ . Counterproductive work behaviour had  $M = 1.11$ ,  $SD = 0.67$ . These values reflect moderate task and contextual performance and low engagement in counterproductive acts (Koopmans *et al.*, 2014).

Li and Wang (2021) analysed specific stressors among university teachers. Techno-complexity and techno-insecurity were negatively associated with work performance. Techno-overload showed a positive association with performance (Li & Wang, 2021). Additionally, technostress inhibitors such as involvement facilitation and technical support provision helped reduce specific technostress creators; however, literacy facilitation contributed to increased technostress, particularly among senior elderly teachers (Li & Wang, 2021).

Kent and Giles (2017) assessed technology self-efficacy using multiple items related to technology integration capabilities. The overall mean score for technology self-efficacy was  $M = 4.6$  ( $SD$  not reported) on a six-point scale, indicating a relatively high level of confidence in using technology. Among the specific items, the highest-rated aspect was integrating technology across the curriculum ( $M = 4.9$ ), while the lowest-rated aspect was implementing technology into lessons ( $M = 3.9$ ). Respondents reported capability in using technology, yet implementation was hindered by external constraints, including limited resources and weak institutional support (Kent & Giles, 2017).

The Proactive Personality Scale, developed by Bateman and Crant, is central to this line of work. The scale produced an average of  $M = 90.7$  and  $SD = 11.4$ , which reflects relatively high proactive behaviour among respondents. It correlated with need for achievement,  $r = 0.45$ ,  $p < .01$ , and need for dominance,  $r = 0.43$ ,  $p < .01$ , which supports its validity for predicting proactive workplace behaviours (Bateman & Crant, 1993).

Age and gender relate to technostress in distinct ways. Older workers report higher levels of technostress, especially techno-complexity (Setyadi *et al.*, 2017; Marchiori *et al.*, 2019; Leitner & Rašticová, 2024). Gender patterns also appear. Women report higher overall technostress, techno-complexity and techno-uncertainty. Men report

higher techno-overload and techno-invasion (Marchiori *et al.*, 2019; Leitner & Rašticová, 2024). Some studies report no gender differences (Agbu & Simeon, 2011). Men are more susceptible to achievement-related stress linked to technology use (Riedl *et al.*, 2013). Feeling younger than one's chronological age lowers technostress, a cognitive age effect (Setyadi *et al.*, 2017). Technostress reduces job satisfaction and performance and lowers intention to continue using technology (Setyadi *et al.*, 2017; Carlotto & Wendt, 2016). Senior-ranking employees experience more techno-overload and techno-invasion (Leitner & Rašticová, 2024). These patterns point to the need to account for individual differences when addressing technostress at work.

Research on individual work performance highlights related age and gender effects. Age diversity supports organisational performance. Employees over 50 show higher work engagement, especially absorption and dedication (Roy, 2022). Gender relates to task execution. Females display stronger multitasking efficiency with fewer errors (Crews & Russ, 2020). Gender representation in leadership and the broader workforce links positively to organisational performance (Park, 2020). Performance appraisal justice predicts affective commitment, with stronger effects for older and female employees (Rana & Singh, 2021). Job satisfaction strengthens organisational citizenship behaviour and task performance across genders (Casu *et al.*, 2021). These results matter as workforces age globally and as organisations manage human capital more deliberately (Beier *et al.*, 2022).

Technology self-efficacy (TSE) shows complex ties to age and gender. Gender roles, especially masculinity, shape technology self-efficacy more than biological sex alone (Huffman *et al.*, 2013). Age and gender influence self-efficacy development and training success. Older women show more positive outcomes than older men (Bausch *et al.*, 2014). Gender differences in teachers' ICT self-efficacy are more pronounced among older educators and minimal among younger educators (Šabić *et al.*, 2021). Both gender and generation predict technology efficacy among secondary teachers (Woods *et al.*, 2021). Younger individuals (18-25 years old) report higher levels of technological proficiency and self-efficacy (McCoy, 2010). However, the relationship between computer self-efficacy and information privacy concerns varies across age groups and genders (Awwal, 2012). Organisational culture has a limited impact on

computer self-efficacy, with age and gender having a more significant direct influence (Pearson *et al.*, 2003).

Research on proactive personality and its relationships with age and gender reveals complex interactions. Proactive personality is positively associated with job search intensity, particularly among older job seekers (Zacher, 2012; Zacher & Bock, 2014). It also correlates with higher life satisfaction during late career and early retirement (Maurer & Chapman, 2018). Age moderates the relationship between proactive personality and training-related outcomes, with stronger effects for younger individuals (Bertolino *et al.*, 2011). The interplay of age, gender and motives influences others' evaluations of proactive behaviour, with different patterns observed for men and women across age groups (Bohlmann & Zacher, 2021). A proactive personality demonstrates reciprocal relationships with work characteristics over time (Li *et al.*, 2014). It predicts networking intensity among job seekers (Lambert *et al.*, 2006). Age shows a curvilinear relationship with network diversity (Lambert *et al.*, 2006). Developmental opportunities substantially affect self-perceived employability for older workers (Heijden *et al.*, 2015).

## **2.8 MODERATING ROLE OF TECHNOLOGY SELF-EFFICACY AND PROACTIVE PERSONALITY**

Digital work relies on constant technology use, which raises technostress risks (Tarafdar *et al.*, 2019). Identifying variables that weaken the link between technostress and individual work performance is essential for practical interventions. This section examines the moderating roles of technology self-efficacy and proactive personality.

### **2.8.1 Moderating role of technology self-efficacy**

Technology self-efficacy reduces the adverse effects of technostress on performance (Marchiori, Mainardes & Rodrigues, 2019). It reflects beliefs about effective technology use and shapes reactions to techno-stressors (Yener, Arslan & Kiliç, 2021). Employees with high technology self-efficacy tend to frame stressors as challenges, cope better and sustain performance (Kim & Lee, 2021). Building technology self-efficacy is, therefore, a practical route to protect individual work performance (Qi, 2019). Qualitative evidence from a technology firm shows that higher perceived self-

efficacy helps new knowledge workers manage technostress (Andreou, 2019). A recent review grounded in social cognitive theory reports lower technostress among employees with higher computer self-efficacy (Yang *et al.*, 2025).

### **2.8.2 Moderating role of proactive personality**

Technostress relates negatively to performance across studies (Tiwari, 2020; Tarafdar, 2015; Saleem & Malik, 2023). A proactive personality is marked by the willingness to take initiative and change one's environment (Din *et al.*, 2023). Proactivity reflects behaviours that generate organisational benefits (Crant & Chen, 2024). It also helps employees manage the performance costs of technostress (Tiwari, 2020). In academic settings, proactive staff are more likely to take initiative in the use of digital tools to meet institutional objectives (Parker, Wang & Liao, 2019). Proactivity can serve as a protective mechanism that supports adaptation to technological change and sustains performance (Tarafdar *et al.*, 2019; Tiwari, 2021). Not all outcomes are positive. Proactive behaviour can create leadership challenges by shaping influence dynamics among employees and managers (Chen & Haga, 2022). Even so, evidence points to net benefits. Proactive employees adapt better to technological stressors and show improved performance (Wang *et al.*, 2022). Joint effects also matter. High technology self-efficacy combined with a proactive personality is associated with greater resistance to technostress and better performance (Li *et al.*, 2023). Organisations should develop both attributes and assess their combined impact in technology-intensive contexts.

## **2.9 SYNTHESISING GAPS IN THE LITERATURE**

Scholarship on technostress and performance is substantial, yet key gaps remain. The field lacks a comprehensive framework that captures the multifaceted nature of technostress and integrates individual and organisational factors in a single model (Ficapal-Cusí *et al.*, 2025; Moko, Victor-Ikoh & Okardi, 2023; El Kiassi & Jahidi, 2023). A unified approach that includes proactive personality and technology self-efficacy is needed to explain variation in individual work performance.

Moderators are understudied. Prior work calls for closer examination of individual characteristics that alter technostress–performance links, with specific attention to

technology self-efficacy and proactive personality (Srivastava *et al.*, 2015; Saidy, Garanti & Sadaka, 2022; Tiwari, 2021; Yener *et al.*, 2021). Context also matters. Technostress is context-specific, and its long-term effects in higher education remain under-examined (Nastjuk *et al.*, 2023). Many studies focus on health, sales and information systems, which leaves a gap in academic workplaces (Pullins, Tarafdar & Pham, 2020; Rohwer *et al.*, 2022; Nastjuk *et al.*, 2023).

Developing-country settings are under-represented. Technostress is emerging across these contexts, and slower technology adoption can intensify performance risks (Rafsanjani *et al.*, 2023). Managers in higher education need evidence on the “dark side” of technology and its effects on employees. This study focused on an African university to address this gap.

Finally, organisational setting effects require deeper analysis. Work design, resources and support systems shape technostress responses and performance outcomes (Harunavamwe & Kanengoni, 2023). Research in higher education should specify contextual features and ensure that the findings are applicable to similar institutions across the African region and other developing economies.

## **2.10 CONCEPTUAL FRAMEWORK: RELATIONSHIP BETWEEN TECHNOSTRESS, WORK PERFORMANCE AND THE MODERATING ROLES OF TECHNOLOGY SELF-EFFICACY AND PROACTIVE PERSONALITY**

Based on a review of the literature and discourse in this field, this section presents a concise framework that links technostress to the work performance of academic staff (Khuzaini *et al.*, 2021). It demonstrates how two personality traits (i.e., proactive personality and technology self-efficacy) influence the relationship between technological stress and work performance. The framework draws on Social Cognitive Theory (Bandura, 1986) and the Transactional Model of Stress and Coping (Lazarus & Folkman, 1984).

Technostress is the strain one feels when digital demands exceed one’s ability to cope with them. It appears as techno-overload, techno-invasion, techno-complexity, techno-insecurity or techno-uncertainty (Tarafdar *et al.*, 2007; Ragu-Nathan *et al.*,

2008). These five stressors describe working too fast, staying always connected, facing complex systems, fearing job loss and handling constant updates. Individual work performance (IWP) refers to the quality and quantity of teaching, research and administration of academics. High technostress drains attention and energy, leading to a decline in productivity (Khuzaini *et al.*, 2021).

TSE and a proactive personality buffer this process. Academics with strong TSE trust their ability to use technology (Lo, Tian & Ng, 2021). These academics treat new digital tools in their workplace as challenges rather than threats. A proactive personality encourages staff to identify problems early, seek solutions and adjust workflows before stress escalates (Crant & Chen, 2024; Yener, Arslan & Kiliç, 2021).

Social Cognitive Theory explains the power of self-belief and deliberate action (Bandura, 1986). The Transactional Model suggests that stress effects depend on appraisal and coping resources (Lazarus & Folkman, 1984). Together, these theories clarify why capability and disposition can alleviate technostress.

The framework predicts three outcomes. First, higher technostress is associated with lower performance (Ayyagari *et al.*, 2011). Second, a strong TSE mitigates that decline (Mahapatra, 2018). Third, a proactive personality also reduces the drop in performance (Sarabadani *et al.*, 2018). Testing these predictions will show which buffer works best.

Managers can act now by offering hands-on digital skills courses to boost TSE (Chen & Muthitacharoen, 2016); encouraging initiative through mentoring and autonomy (Yener *et al.*, 2021); and designing systems that avoid needless complexity and 24/7 intrusion to tackle stress at its source (Ayyagari *et al.*, 2011). These steps reduce technostress and protect academic performance.

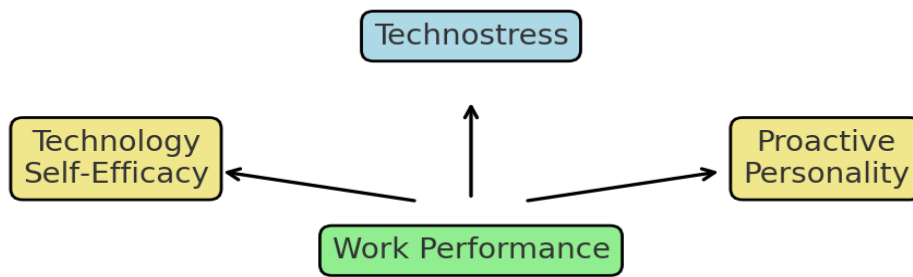


**Figure 2.1: Conceptual framework**

### **2.11 SUMMARY**

The literature review identified the reasons behind the formation of technostress and its effect on IWP among academics in the higher education space. The chapter also defined the concepts of technostress, IWP, proactive personality and TSE. Several studies have explored the role of personality factors in moderating the relationship between technostress and work performance. The literature review discussed the moderating effects of technology self-efficacy on the relationship between technostress and work performance. Scholars argue that a proactive personality can be viewed as a key moderator, explicitly highlighting its role in mitigating the negative impact of technostress on work performance. This chapter also identified the prevalent theories relating to work performance and technostress that guided the formulation of a proposed conceptual framework for this study. The next chapter presents the methodology underpinning the study.

## CHAPTER 3

### RESEARCH METHODOLOGY AND DESIGN

#### 3.1 INTRODUCTION

This chapter sets out the research methodology used to examine the influence of technostress on staff academic work performance in a higher education institution. Sound methods support scientific enquiry and credible findings (Dunn, 2018). A transparent methodology strengthens reliability and validity (Dunn, 2018). The chapter states the research philosophy that guided knowledge development. It then explains the research design, the target population, and the sampling strategy. It describes the instruments, the data collection procedures, and the data sources. The chapter concludes with the data analysis methods, the ethical standards followed, the procedures used to establish instrument reliability and validity, and the study limitations.

#### 3.2 RESEARCH PHILOSOPHY

Research is a systematic and creative work that expands knowledge and supports practical application (Winit-Witjana, 2016). Research philosophy sets out the beliefs and assumptions that guide knowledge development (Žukauskas, Vveinhardt, and Andriukaitienė, 2018). Researchers should weigh philosophical and practical issues before a project begins, given the diversity of research activities and emerging perspectives (Illing and Carter, 2018).

Core philosophical elements shape the approach and the outcomes. Ontology concerns the nature of reality and what exists for inquiry (Saunders, 2014). Epistemology concerns what counts as acceptable knowledge and how we know it to be true (Sol and Heng, 2022). Axiology concerns the role of values and ethics in research choices and conduct (Edelheim *et al.*, 2022). Logic of enquiry links these elements to coherent reasoning across the study. Researchers need to understand these terms, select an approach that fits the problem, and justify the choice in the study context (Saunders, 2014).

These choices influence the whole project. They shape the design, the selection of methods, the form of data, the analysis, and the interpretation of results (Panya and Nyarwath, 2022). Research paradigms bring these philosophical positions together into broader worldviews. A paradigm integrates ontological and epistemological assumptions with methodological strategies and techniques (Creswell and Clark, 2017). In this sense, philosophy and paradigm are linked. Philosophy focuses on assumptions about reality and knowledge. Paradigm couples those assumptions with a way of doing research in practice (Illing and Carter, 2018). Precise alignment between philosophy, paradigm, design, and methods supports internal consistency and strengthens the contribution of the study (Panya and Nyarwath, 2022).

This study was based on positivism. The positivist paradigm asserts that the social world is objective and that reality exists independently of individuals. It emphasises empirical, observable social reality, measurable phenomena and the pursuit of generalisable laws and patterns (Khanday, 2024). The positivist approach adheres strictly to the scientific empirical method designed to generate accurate facts and data free from human bias or ambiguous interpretation (Creswell & Clark, 2017). Positivism considers the measurement of phenomena as central to the development of understanding and therefore emphasises the importance of observation for the growth of knowledge. The positivist research paradigm has been both defended and critiqued in the literature. Park, Konge and Artino (2019) argue for its use, with the latter suggesting that even its critics are logically committed to propositions that can only be tested using positivist paradigms. Some scholars challenge its dominance, particularly in education and nursing research (Panhwar, Ansari & Shah, 2017; Corry, Porter & McKenna, 2019). Panhwar *et al.* (2017) advocate for a shift towards post-positivism, which incorporates aspects of pluralism and critical multiplicity. Corry *et al.* (2018) hold that post-positivism has superseded positivism as the guiding paradigm for the scientific method.

Research paradigms are essential when conducting and interpreting research. Researchers must choose a paradigm that considers the nature of the research aims and objectives, as well as their values and personal beliefs regarding what constitutes knowledge and reality. Furthermore, researchers choose a paradigm based on the nature and specific context of the study. As such, this study employed a positivist

paradigm to investigate whether technostress affects individual work performance and to further examine the moderating roles of proactive personality and technology self-efficacy in this relationship. The positivist paradigm is ideal for business studies, wherein hypothesis verification is the foundation of the study (Ali, I., 2024). The positivist research paradigm allowed the researcher to objectively establish the influence of technostress on work performance in the South African higher education context.

### **3.3 RESEARCH METHODOLOGY**

Methodology refers to the systematic processes and procedures used to collect and analyse data. Consistency in methodology, data collection and analysis can help improve the study's reliability and validity (Coleman, 2022). In this study, we adopted the quantitative research design to collect and analyse data on the influence of technostress on work performance (Finkbeiner & Finkbeiner, 2017).

It is rooted in the pursuit of factual information and aims to provide universal value. Some authors consider the quantitative approach the epitome of the scientific approach (Quick & Hall, 2015). Leavy (2022) maintains that the quantitative approach has been widely adopted as it involves the use of two well-known designs: the experimental and non-experimental research designs. The experimental design helps manipulate key variables, whilst the non-experimental design employs data collected from respondents to answer research questions. Another key element that makes the quantitative research design stand out is that it allows a larger sample size. This renders the quantitative design suitable for several research endeavours, such as involving community members (Quick & Hall, 2015).

Another advantage of quantitative studies is that they often have a significantly larger sample size than projects using the qualitative approach, making them more applicable to a broader community, as researchers can employ various sampling techniques to ensure fair representation of respondents (Quick & Hall, 2015). Gorard (2010) underscores the applicability of the quantitative approach, citing the availability of diverse methods and sampling techniques at the researcher's disposal, which leads to research rigour.

Taherdoost (2022) argues that the selection of a specific research approach yields few advantages and disadvantages. The researcher, therefore, chooses the approach that is more suitable for answering the research questions under study (Taherdoost, 2022). Demirli and Turel (2012) postulate that although the qualitative approach can be used to interpret research findings in educational research, it cannot quantify the identified effects that are crucial in academic research. In support of this notion, Hatch (2023) argues that it is critical to quantify the identified impact in educational research, a task that qualitative research often fails to accomplish. Furthermore, the quantitative approach allows a range of multivariate analyses, which helps identify research results that can be generalised to other populations (Lazar *et al.*, 2016). Quantitative approaches suit many social scientists because they allow clear, testable objectives based on verifiable data (Turan, 2014). Evidence points to several strengths. They handle large samples, model relationships between constructs, and estimate the contribution of variables to outcomes (Lazar *et al.*, 2016). They also support the classification of respondents into categories, which gives a more precise interpretation of findings (Hatch, 2023). In studies on technostress, this approach presents staff perceptions in numbers and figures, which helps you see patterns across academic units.

Limits remain. Quantitative results describe the size and direction of effects, not the underlying reasons. Scale validation before data collection is often required to secure reliable results, which extends timelines. Abnormal distributions also arise. In factor analysis, items with communalities of 0.5 or lower are typically removed, which risks losing insight. You should weigh these trade-offs before selecting a quantitative design for work performance studies on technostress.

### **3.4 RESEARCH DESIGN**

Research design is the structured plan that directs how a study collects and analyses data (Quinlan *et al.*, 2019). This study employs a cross-sectional correlational design to examine the association between technostress and individual work performance among academics in a higher education institution. Data collection occurs at a single point in time. The approach offers a clear snapshot of levels of technostress and performance during the survey window.

A cross-sectional design gathers information from a defined population once, which supports efficient estimation of prevalence and description of population characteristics (Zuleika, 2022). The design suits studies that explore relationships between variables without tracking participants across periods. Prior research has applied cross-sectional surveys to conceptualise technostress in university student populations and among organisational end users, which supports methodological fit for academic staff as a target group (Abd Aziz and Yazid, 2021; Hyojin, Baeyoung and Jaesam, 2016). The approach aligns with population-based surveys and stress prevalence assessments where breadth, economy, and timely fieldwork matter. It also avoids loss of respondents over time, an issue that weakens longitudinal studies, especially in developmental contexts (Savitz and Wellenius, 2023).

The design offers several strengths for this study. It provides point estimates of technostress prevalence in the academic workforce. It enables tests of associations between technostress dimensions and work performance outcomes with adequate statistical power when the sample is large. It supports subgroup comparisons across faculties and academic ranks during the same period, which limits period effects.

The design also imposes limits that require careful handling. Cross-sectional data do not establish temporal order. Findings, therefore, address associations rather than causes. Self-report measures introduce response bias. The study addresses this risk using validated scales, clear instructions, and confidentiality safeguards. Single-wave surveys may exhibit non-normal item distributions. The analysis plan includes data screening, use of robust estimators, and transparent reporting of any item removal rules, including communality thresholds where factor models apply. These safeguards strengthen the credibility of the estimates while keeping the design aligned with the study's aim and resource constraints. This research design selects the entire population or a subset of it. Data are collected from the selected individuals through a survey questionnaire to help answer research questions. This design is called cross-sectional because the information gathered about individuals represents what is happening only at a specific point in time (Olsen & St George, 2004). For instance, this study attempted to determine, through a cross-sectional design, whether there was a relationship between technostress and the individual work performance of academics,

as it hypothesised that academics with a high prevalence of technostress did not perform optimally at work due to challenges with technology integration.

The adoption of a cross-sectional correlational design may address temporal and resource constraints. Given the time and resource limitations of doctoral research, a cross-sectional correlational design offers a pragmatic approach to data collection and analysis. Cross-sectional data enable comparative analyses across different demographic groups, geographic regions or other relevant categories, enhancing the breadth and depth of insights derived from the study (Olsen & St George, 2004).

This cross-sectional correlational design enables simultaneous examination of multiple variables—technostress, individual work performance, proactive personality, and technology self-efficacy—within a defined academic population at a single point in time, providing a structured snapshot of the phenomenon (Quinlan *et al.*, 2019; Zuleika, 2022). The approach supports estimation of prevalence, description of subgroup differences, and testing of associations and moderation effects in one survey window (Zuleika, 2022).

The design has recognised limits. It does not establish temporal order, so causal claims are not warranted (Sobol, 2014). Single-wave surveys are also vulnerable to recall bias and cannot capture change over time (Satten & Grummer-Strawn, 2005). Within these constraints, the design remains fit for the study aim. It offers an efficient framework to investigate links between technostress and work performance and to assess whether proactive personality and technology self-efficacy weaken these links in the measured period, adding evidence to the academic context under study (Quinlan *et al.*, 2019; Zuleika, 2022).

### **3.5 POPULATION**

Determining the research population is a central step in quantitative studies. The choice fixes who qualifies to answer the research questions and shapes the validity of any generalisation to a broader group. A research population refers to the group of potential respondents targeted to address the study objectives (Hossan, Dato'Mansor, & Jaharuddin, 2023). Classic texts define the population as the source from which a sample is drawn for analysis (Babbie & Mouton, 2015). Broader views include discrete

populations defined by geography, race, income, or disease, depending on the topic and the aims of inference (Arias-Gómez, Villegas, and Miranda-Novales, 2016). A clear definition also serves ethics and applicability. Precise population boundaries guide eligibility and determine how far results apply to other groups (Eldredge, Weagel & Kroth, 2014).

The present study targets academic staff members employed at a University of Technology located in Gauteng. The unit of analysis is the individual academic employee. The population includes staff engaged in teaching and learning, such as full-time and part-time lecturers, as well as researchers who teach. The University's annual report of December 2022 records 2,289 academic staff members across seven campuses, which offers a finite frame for sampling and response tracking in fieldwork. These figures supply context for representativeness and power when planning the required number of responses for analysis.

Inclusion and exclusion rules follow methodological guidance on selecting populations with shared characteristics relevant to the study purpose (Creswell, 2017). Inclusion covers academics involved in core teaching and learning activities during the survey window. Exclusion covers staff in purely administrative roles without teaching duties. These rules align the population with the constructs under study, namely, technostress and individual work performance in academic work.

This definition supports clarity, feasibility, and ethical rigour. It provides a concrete framework for recruitment and a transparent basis for generalising findings to the broader academic workforce within the institution. It also aligns the study questions with the people best positioned to answer them, which improves construct validity and strengthens the interpretability of the results in the higher education context (Hossan *et al.*, 2023; Babbie and Mouton, 2015; Arias-Gómez *et al.*, 2016; Eldredge *et al.*, 2014; Creswell, 2017).

### **3.6 SAMPLING STRATEGY**

Sampling determines who provides data and how far findings apply. It refers to the subset of respondents selected from the target population to answer the research questions (Maree, 2016). Appropriate sample size strengthens validity and reliability

because estimates become more stable and measurement error decreases (Rendón-Macías and Villasís-Keever, 2017). Researchers must also balance precision with feasibility. Oversized samples waste resources, while undersized samples weaken statistical power and inflate the risk of Type II error (Jobst, Bader, and Moshagen, 2023).

This study drew the sample using simple random sampling. Each eligible academic had an equal probability of selection, which reduces selection bias and supports unbiased estimation under standard assumptions (Maree, 2016; Noor, Tajik, and Golzar, 2022). The higher education setting includes a diverse workforce aligned with employment equity requirements. Random selection is therefore appropriate because it gives all subgroups a chance to be included and supports fair representation across faculties and ranks (Noor *et al.*, 2022; Saini, Jitendrakumar, and Kumar, 2022).

The achieved sample comprised 304 academic staff members drawn from the institution's eight faculties. The size was determined with the Raosoft sample size calculator at a 95 percent confidence level. The resulting sample supports the planned analyses, including partial least squares, structural equation modelling, and multiple mixed regression, given published guidance on minimums for complex multivariate models (Chomeya *et al.*, 2024). Conventional thresholds for covariance-based SEM often range from 100 to 150 cases, which places this study comfortably above the lower bounds for stable estimation, while still permitting subgroup comparisons when design effects are monitored (Chomeya *et al.*, 2024).

The sampling plan aligns the research aim with methodological standards. Clear inclusion rules, random selection, and an adequate sample size support credible estimates and strengthen the interpretability of relationships among technostress, individual work performance, proactive personality, and technology self-efficacy in the academic context (Maree, 2016; Rendón-Macías and Villasís-Keever, 2017; Jobst *et al.*, 2023; Noor *et al.*, 2022; Saini *et al.*, 2022; Chomeya *et al.*, 2024).

### **3.7 DATA COLLECTION METHODS**

Data collection in quantitative research is the systematic gathering of raw data from respondents with a pre-defined instrument aligned to the study objectives (Taherdoost,

2021). The researcher must describe the procedures clearly. This includes the variables measured, the instruments applied, and the forms used to capture responses, so that the resulting dataset is reliable and valid (Brink *et al.*, 2018, p. 133). Precision at this stage improves accuracy and reduces avoidable error in later analysis (Mazhar *et al.*, 2021).

This study surveyed academic staff through an online questionnaire built on Microsoft Forms. The Chief Information Officer granted permission to distribute the survey to academic employees in all eight faculties. The invitation included a brief introduction that stated the study's aim and the ethics approval reference REC/2023/05/011. The instrument collected no personal identifiers. It did not request staff numbers, identity numbers, names, or surnames. The CIO's office sent the survey link and periodic reminders via the institutional email system.

Fieldwork took place between May 2023 and December 2024. After closure of the survey window, responses were exported to Microsoft Excel and then imported into Stata for analysis. The dataset was cleaned and coded at the item level to support descriptive statistics, scale reliability checks, and multivariate modelling. These steps align with guidance on transparent, replicable procedures that protect data quality from collection through to analysis (Taherdoost, 2021; Brink *et al.*, 2018; Mazhar *et al.*, 2021).

### **3.8 RELIABILITY AND VALIDITY OF THE MEASURING INSTRUMENTS**

Establishing the quality of measurement is central to quantitative enquiry. Instruments must be both reliable and valid to support credible inference (Ganesha & Aithal, 2022). Reliability and validity are the core criteria used to judge data-collection tools before, during, and after fieldwork (Vakili & Jahangiri, 2018).

Validity addresses whether an instrument measures what it is intended to measure. Two forms are primary in this study. Construct validity concerns the degree to which items capture the theoretical construct of interest (Lim, 2024). Content validity concerns the extent to which the item set adequately represents the domain being measured (Mohajan, 2017). These properties are commonly evaluated with factor-analytic techniques. Exploratory and confirmatory factor analysis test item loadings,

factor structure, and overall model fit to substantiate the intended constructs (Vakili & Jahangiri, 2018). Detailed validity results for the instruments used here are reported in Chapter 4.

Reliability addresses the stability and internal coherence of the measurements. Internal consistency reliability examines whether items that form a scale are interrelated and reflect the same latent construct (Hajjar, 2018). Cronbach's alpha is the most widely used coefficient for this purpose and is reported for each multi-item scale in this study (Hajjar, 2018). By combining documented forms of validity with evidence of internal consistency, the study strengthens the interpretability of estimates derived from the survey measures and supports the robustness of the findings (Ganesha & Aithal, 2022; Vakili & Jahangiri, 2018).

The use of Cronbach's alpha, or alpha value, has become popular in educational research. Cronbach's alpha is extremely valuable in indicating scale dependability regarding the comparability and equivalence of items within single-construct scales. Alpha values are expressed between 0 and 1, where the closer the value is to 1, the more reliable the construct. In addition to this, Fraenkel, Wallen and Hyun (2015) posit that to be considered reliable, an instrument must yield alpha values between 0.70 and 0.90 with at least 25 participants completing the instrument. The research instrument used in this study demonstrated good reliability measures, as indicated by both the developers of the scales and subsequent studies that adopted them. Table 3.1. depicts the Cronbach's alpha values of the developers of the scales used in this study.

**Table 2.1: Reliability findings by the developers of the scales**

| Scale/Constructs                     | Authors                    | Number of Items | Cronbach's alpha values |
|--------------------------------------|----------------------------|-----------------|-------------------------|
| <b>Technostress Scale (23 items)</b> |                            |                 |                         |
| Techno-Overload                      | Fuglseth and Sørebo (2014) | 6               | 0.88                    |
|                                      | Jena and Mahanti (2014)    |                 | 0.83                    |
| Techno-Invasion                      | Jena and Mahanti (2014)    | 3               | 0.87                    |
| Techno-Complexity                    | Jena and Mahanti (2014)    | 5               | 0.82                    |
| Techno-Insecurity                    | Jena and Mahanti (2014)    | 4               | 0.78                    |

| Scale/Constructs                                                    | Authors                   | Number of Items | Cronbach's alpha values |
|---------------------------------------------------------------------|---------------------------|-----------------|-------------------------|
| Techno-Uncertainty                                                  | Nimrod (2018)             | 5               | 0.87                    |
|                                                                     | Jena and Mahanti (2014)   |                 | 0.83                    |
| Individual Work Performance Scale (18 items)                        |                           |                 |                         |
| Task performance (TP) scale                                         | Mayangsari (2020)         | 6               | 0.70                    |
|                                                                     | Zeglat and Janbeik (2019) |                 | 0.78                    |
| Contextual performance (CP) scale                                   | Mayangsari (2020)         | 6               | 0.71                    |
|                                                                     | Zeglat and Janbeik (2019) |                 | 0.76                    |
| Counterproductive Work Behaviour (CWB) scale                        | Mayangsari (2020)         | 6               | 0.78                    |
| Technology Self-Efficacy Scale                                      |                           |                 |                         |
| Facilitate and Inspire Student Learning                             | Saville and Foster (2021) | 6               | 0.70                    |
|                                                                     | Simsek and Yazar (2016)   |                 | 0.83                    |
| Design and Develop Digital-Age Learning Experiences and Assessments | Saville and Foster (2021) | 6               | 0.70                    |
|                                                                     | Simsek and Yazar (2016)   |                 | 0.87                    |
| Model Digital-Age Work and Learning                                 | Saville and Foster (2021) | 6               | 0.70                    |
|                                                                     | Simsek and Yazar (2016)   |                 | 0.77                    |
| Promote and Model Digital Citizenship and Responsibility            | Saville and Foster (2021) | 6               | 0.70                    |
|                                                                     | Simsek and Yazar (2016)   |                 | 0.78                    |
| Engage in Professional Growth and Leadership                        | Saville and Foster (2021) | 6               | 0.70                    |
|                                                                     | Simsek and Yazar (2016)   |                 | 0.85                    |
| Proactive Personality Scale                                         |                           |                 |                         |
| All items on the scale                                              | Kim and Park (2017)       | 14              | 0.82                    |

### 3.8.1 Technostress measuring instrument

The study used established instruments with published evidence of validity and reliability. Technostress was measured with the scale first developed by Tarafdar *et*

*al.* and later adapted by Chen for knowledge workers in a developing economy context that aligns with South Africa (Tarafdar *et al.*, 2007; Chen, 2015; Le Roux and Botha, 2021). Chen's version contains 22 items on a five-point Likert scale (Chen, 2015).

Evidence supports the psychometric strength of this adaptation. Chen reported acceptable confirmatory factor analysis results, with RMSEA 0.06, CFI 0.94, RMR 0.05, and GFI 0.91. Item loadings were statistically significant at  $p < 0.001$ , which supports construct validity (Chen, 2015). Further studies report consistent findings across university contexts. In Spain, validation with university students confirmed the model using exploratory and confirmatory procedures. Sampling adequacy was excellent, with KMO 0.950 (Penado Abilleira *et al.*, 2020). In China, work on technology-enhanced learning produced strong internal consistency for the full scale with Cronbach's alpha of 0.942. A shortened twenty-item form also returned an alpha of 0.939 (Wang, Tan, and Li, 2020). Additional studies reported alpha coefficients of 0.87 and 0.83, which remain acceptable for research use (Nimrod, 2018; Jena and Mahanti, 2014).

Taken together, these results show a coherent factor structure, strong internal consistency, and transportability across settings. The Chen adaptation is therefore appropriate for assessing technostress among academic staff in this study's context (Chen, 2015; Le Roux and Botha, 2021; Penado Abilleira *et al.*, 2020; Wang *et al.*, 2020). The choice aligns the study aims with an instrument that measures the construct with precision and stability.

### **3.8.2 Individual Work Performance Measuring Instrument**

The study used established, psychometrically sound instruments to measure the focal constructs. Choices were guided by evidence on validity, reliability, and suitability for higher education settings where organisational decisions require defensible data (van der Vaart, 2021).

Individual work performance served as the dependent variable and was measured with the Individual Work Performance Questionnaire. The IWPQ specifies three second-order dimensions, namely task performance, contextual performance, and counterproductive work behaviour. The instrument contains 18 items scored on a five-

point Likert scale (Koopmans, 2011a; Koopmans, 2014b). The original development programme reported multiple forms of validity. Evidence covered face validity, structural validity, and convergent validity through correlations with the World Health Organisation's performance questionnaire (Koopmans, 2011a). Subsequent applications support generalisability. Studies from Turkey and Vietnam reported satisfactory validity and reliability in occupational samples, which indicates stability across contexts (Develi and Çavuş, 2024; Nguyen Duc *et al.*, 2024). Work in South Africa showed that a three-dimensional model provided a better fit than a four-dimensional model under Rasch analysis. That programme identified generic items that functioned well across sectors and produced a streamlined 14-item version known as IWPQ 0.2. Person item maps suggested the need for sharper discrimination at the higher end for task performance and at the lower end for counterproductive work behaviour. Iterative refinements maintained validity and reliability while improving targeting (van der Vaart, 2021; Koopmans, 2014b). Additional studies also reported solid performance. A cross-cultural American English evaluation produced Cronbach's alpha values between 0.79 and 0.89 across constructs and supported content validity (Koopmans *et al.*, 2016). Exploratory structural equation modelling indicated adequate fit for job performance with an emphasis on behaviours directed at the organisation (Pedro *et al.*, 2019). Other reports placed alpha between 0.70 and 0.78, which is acceptable for research use (Mayangsari, 2020; Zeglat and Janbeik, 2019). Evidence from Indonesia added further support. Aiken's V values ranged from 0.87 to 0.91 for content relevance, Cronbach's alpha reached 0.94, Rasch person reliability was 0.87, Rasch item reliability was 0.98, and confirmatory factor analysis produced RMSEA 0.08 and CFI 0.96 (Saviera *et al.*, 2021). Taken together, these findings justify the IWPQ as an appropriate measure for this study's aims and sample.

### **3.8.3 Technology Self-efficacy Measuring Instrument**

Technology self-efficacy was assessed with the Educator Technology Self-Efficacy instrument. The ETSE measures confidence in using technology for teaching and includes 12 items (Gentry *et al.*, 2014). The original development reported Cronbach's alpha of 0.958, which signals excellent internal consistency (Gentry *et al.*, 2014). Independent applications in higher education confirmed strong psychometric properties in diverse settings (Gomez Jr *et al.*, 2022; Kaqinari *et al.*, 2022; Henderlite,

2023; Örgüt, Korkmaz, and Çakir, 2024). Studies aligned to education for sustainable development and technology standards reported sound validity and reliability, which supports transfer to related teaching contexts (Malandrakis *et al.*, 2018). Research on technology use and computer self-efficacy also reported high validity and reliability for ETSE-based measures (Doğru, 2017; Şendurur and Yıldırım, 2019). A focused validation reported concurrent validity at  $r$  equals 0.83 with a related scale, Cronbach's alpha 0.95, and McDonald's omega 0.96. Corrected item total correlations exceeded 0.30 for both prospective teachers and in-service teachers. These results support both convergence and internal coherence (Simsek and Yazar, 2016). The accumulated evidence indicates that the ETSE is suitable for measuring technology self-efficacy in academic staff.

#### **3.8.4 Proactive Personality Measuring Instrument**

Proactive personality was measured with the Proactive Personality Scale. The PPS contains 17 items and assesses the general tendency to initiate change and influence situations (Bateman and Crant, 1993). Validation studies show consistent reliability and beneficial predictive properties across settings. A six-item version functioned as a reliable unidimensional measure in Ghana (Teye Kwadjo and De Bruin, 2022). Evidence from China linked the PPS to organisational citizenship behaviours tied to proactivity, which supports predictive validity (Hu *et al.*, 2021). A multi-company psychometric study reported reliable and consistent scores in applied settings (Gottenborg, Hoff, Rydstedt, and Øvergård, 2022). A tripartite proposal covering perception, implementation, and perseverance showed satisfactory reliability. It explained task performance variance comparable to the original PPS, which opens space for refined modelling without loss of measurement quality (Belwalkar, 2018). Research has linked proactive personality to career decision making, self-efficacy, and career search self-efficacy, as evidenced by regression models confirming predictive relations (Kim and Park, 2017). Recent commentary also supports the PPS as a suitable indicator of proactive behaviour in academic workplaces (Kilic *et al.*, 2024).

### **3.9 DATA ANALYSIS**

Quantitative data analysis involves examining and interpreting the relationships among variables in the gathered data (Kotronoulas *et al.*, 2023). When conducting

data analysis, it is crucial to consider the study's primary research objective. The following data analysis statistical methods were employed to address the research questions and achieve the goals.

| Research Objective                                                                                                                                         | Statistical Methods Used                                                                             | Detailed Application of Statistical Techniques                                                                                                                                                                                                                                                                                          |
|------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| To establish mean scores of technostress, individual work performance, technological self-efficacy, and proactive personality among academic staff.        | Descriptive Statistics (Mean, SD, Min, Max)                                                          | Computed mean scores, standard deviations, minimum and maximum values for constructs, with results interpreted using calibrated Likert-scale categories.                                                                                                                                                                                |
| To establish differences in technostress, individual work performance, technological self-efficacy, and proactive personality between gender groups.       | Kruskal-Wallis Test, Mann-Whitney U Test                                                             | Kruskal-Wallis test evaluated overall differences between gender groups, while Mann-Whitney U tests specifically assessed pairwise (male vs female) differences. $\chi^2$ , rank sums, U-values, and p-values reported.                                                                                                                 |
| To investigate differences in technostress, individual work performance, technological self-efficacy, and proactive personality across various age groups. | Kruskal-Wallis Test, Dunn's Pairwise Comparison (Bonferroni Adjustment)                              | Kruskal-Wallis test assessed overall differences among age groups; post-hoc Dunn's Pairwise Comparisons (Bonferroni corrected) identified specific significant age-group differences, reporting adjusted p-values.                                                                                                                      |
| To establish the relationship between technostress and individual work performance.                                                                        | Spearman's Rank Correlation Coefficient (Spearman's rho)                                             | Spearman's rho determined monotonic relationships between technostress and individual work performance dimensions (task, contextual, counterproductive). Results were interpreted using Dancey & Reidy's strength-of-correlation guidelines.                                                                                            |
| To assess the moderating role of technology self-efficacy in the relationship between technostress and academic staff's performance.                       | Multivariate Multiple Regression Analysis (Moderation Analysis with Interaction Terms)               | Multivariate regression tested moderation by including interaction terms (Technostress $\times$ Technology Self-Efficacy) for simultaneous evaluation across multiple dependent performance variables. The analysis involved Wilks' Lambda, Pillai's Trace, and adjusted $R^2$ values.                                                  |
| To assess the moderating role of proactive personality in the relationship between technostress and academic staff's performance.                          | Multivariate Multiple Regression Analysis (Moderation Analysis with Interaction Terms)               | Multivariate regression tested proactive personality moderation, incorporating interaction terms (Technostress $\times$ Proactive Personality), and evaluated moderation simultaneously across multiple dependent outcomes. Multivariate significance was assessed using Wilks' Lambda, Pillai's Trace, $R^2$ , and significance tests. |
| To validate the measurement scales for technostress, individual work performance, technological self-efficacy, and proactive personality.                  | Reliability Analysis (Cronbach's Alpha), Exploratory Factor Analysis (EFA) (KMO and Bartlett's Test) | Reliability was confirmed using Cronbach's alpha for internal consistency. Exploratory Factor Analysis employed Kaiser-Meyer-Olkin (KMO) and Bartlett's tests to confirm data suitability and dimensionality of measurement scales.                                                                                                     |
| To confirm and validate the hypothesised measurement model and factor structure of technostress, individual work performance,                              | Confirmatory Factor Analysis (CFA)                                                                   | CFA explicitly validated hypothesised measurement structures. Model fit indices included Chi-square ( $\chi^2$ ), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and                                                                                                           |

| Research Objective                                                                                                                                                                     | Statistical Methods Used            | Detailed Application of Statistical Techniques                                                                                                                                                                                                                                                                                                                                                    |
|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-------------------------------------|---------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| technological self-efficacy, and proactive personality constructs.                                                                                                                     |                                     | Standardised Root Mean Square Residual (SRMR), confirming convergent and discriminant validity.                                                                                                                                                                                                                                                                                                   |
| To validate and empirically confirm the hypothesised structural relationships among technostress, technological self-efficacy, proactive personality, and individual work performance. | Structural Equation Modelling (SEM) | SEM was explicitly conducted to test and validate structural paths and hypothesised relationships between latent constructs (technostress, technological self-efficacy, proactive personality, and individual work performance). SEM included model fit indices ( $\chi^2$ , CFI, TLI, RMSEA, SRMR), standardised path coefficients, and a detailed evaluation of relationships among constructs. |

### 3.10 ETHICAL CONSIDERATIONS

Researchers are responsible for protecting respondents from harm by adhering to ethical requirements. Researchers must obtain consent from respondents before conducting a study (Leedy & Ormrod, 2014). In this study, informed consent was obtained from the selected university of technology and academic lecturers before the commencement of data collection. As indicated, the data were gathered through an online survey distributed to respondents with the assistance of university's s Chief Information Officer. In doing so, the researcher complied with the Protection of Personal Information (POPI) Act, a South African legislation that protects personal information processed by public and private bodies. The researcher obtained formal permission from the institution's Chief Information Officer to contact academic staff across the eight faculties. Ethical clearance was secured from the research ethics committees of North-West University and the selected University of Technology. The survey invitation was distributed through the institutional email system as a Microsoft Forms link. The landing page presented the study objectives, the consent statement, and the ethics reference REC/2023/05/011. Participation was voluntary. Respondents were informed of the right to withdraw at any time without penalty. The instrument did not request any personal identifiers, including staff numbers, identity numbers, names, or surnames. Completed datasets were stored on a password-protected computer with access restricted to the researcher. These procedures align with guidance on transparent recruitment, informed consent, and data security in quantitative studies, which stresses clear protocols for accuracy and respondent protection (Brink *et al.*, 2018, p. 133; Taherdoost, 2021; Mazhar *et al.*, 2021).

### 3.11 LIMITATIONS

The cross-sectional correlational design fixes measurement at one time point. The design does not establish temporal order. Causal inference is not supported (Sobol, 2014). Single-wave surveys rely on self-reports. This raises risks of standard method variance and socially desirable responding. Changes in technostress over time are not observed, so temporal dynamics remain outside the scope (Satten and Grummer-Strawn, 2005). The study also models only two moderators, technology self-efficacy and proactive personality. Other individual or contextual factors might shape the technostress–performance link and were omitted. Future work should incorporate multiple time points, multi-source data, and a broader set of moderators to strengthen internal validity and extend explanation beyond the present model (Sobol, 2014; Satten and Grummer-Strawn, 2005).

### **3.12 SUMMARY**

This chapter detailed the methodology for assessing the influence of technostress on academic staff performance in a higher education institution. It set out the research approach, paradigm, and cross-sectional correlational design. It described the target population and the sampling frame. It reported the data collection process, including institutional permission, dual ethics approvals, informed consent, and confidentiality safeguards. It explained storage and access controls for the dataset. It also identified design and measurement limits that inform interpretation and point to directions for future research. These procedures and acknowledgements align with recommended practice for rigorous, ethical, and replicable quantitative research (Brink *et al.*, 2018; Taherdoost, 2021; Mazhar *et al.*, 2021)

## **CHAPTER 4**

### **FINDINGS, ANALYSIS AND INTERPRETATION**

#### **4.1 INTRODUCTION**

This chapter presents the findings and interpretation of a study conducted on the influence of technostress on the performance of academic staff at a selected higher education institution. The primary aim of this research was to develop a comprehensive framework for assessing the impact of technostress on the performance of academic staff members. This study sought to attain the following research objectives:

The primary objective is to develop a framework for assessing the influence of technostress on academic staff's performance and the moderating roles of technology self-efficacy and proactive personality in a selected higher education institution. The secondary research objectives are:

- To establish the means scores of technostress, individual work performance, technological self-efficacy and proactive personality of academic staff
- To establish if there are differences in technostress, individual work performance, technological self-efficacy and proactive personality between genders
- To establish if there are differences in technostress, individual work performance, technological self-efficacy and proactive personality between age groups
- To establish if there is a relationship between technostress and individual work performance.
- To assess the moderating role of technology self-efficacy in the relationship between technostress and the performance of academic staff.
- To assess the moderating role of proactive personality in the relationship between technostress and academic staff's performance.

Data for this study were collected through an online survey distributed to academic staff members at the institution. The participants included lecturers, junior lecturers, senior lecturers, associate professors, and professors, all of whom were actively involved in the institution's teaching and learning processes. To facilitate the data collection, permission was obtained from the relevant institutional authorities and designated gatekeepers. A trained fieldworker circulated an online questionnaire to the academic staff, ensuring the process was conducted independently and with high confidentiality.

## **4.2 DEMOGRAPHIC PROFILE OF THE RESPONDENTS**

This section presents the demographic profiles of the respondents. The demographic characteristics presented include age, gender, campus, job level, and the relevant faculty on which the respondents are based.

### **4.2.1 Age group**

The distribution of respondents by age group reveals a relatively diverse range of academic staff, with a significant representation across various age categories. Most respondents fell within the 40-49 age group, accounting for 28.95% of the total sample ( $n = 88$ ). This group was closely followed by the 30- to 39-year-old age group, comprising 27.63% ( $n = 84$ ) of the respondents. These two age categories represent more than half of the respondents (56.58%), indicating that a substantial portion of academic staff are in their mid-career stage and above 30 years of age. Figure 4.1 presents the age group of the respondents who participated in this study.

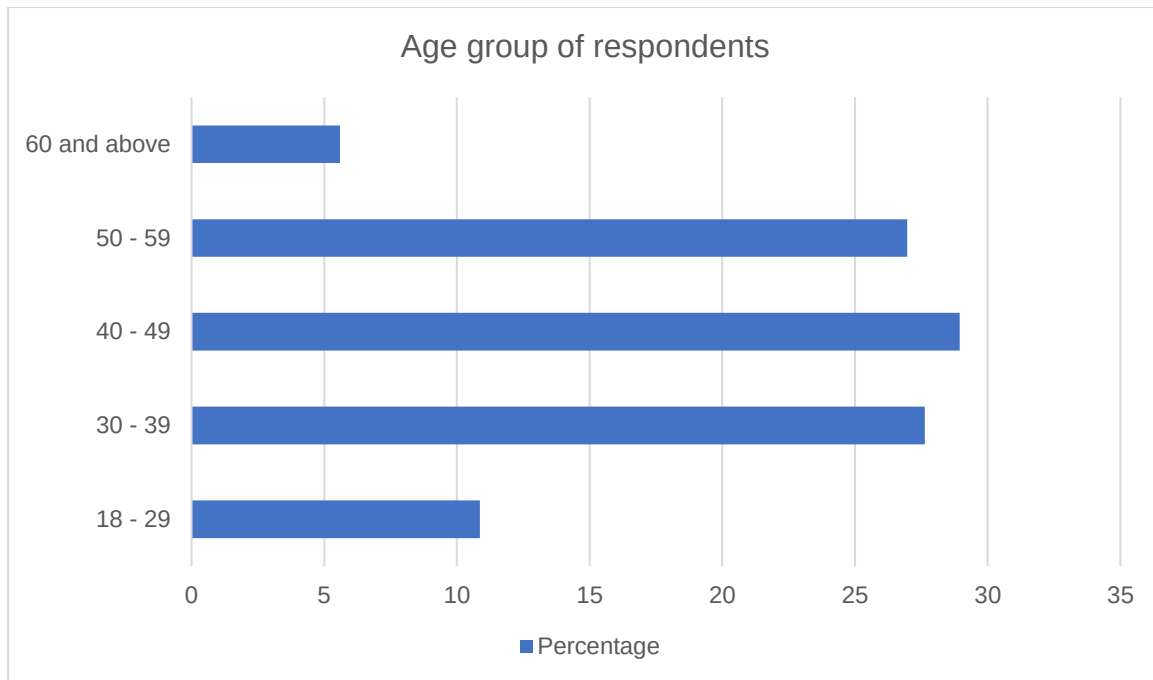


**Figure 4.1: Distribution of age group of the respondents**

In contrast, the 50- to 59-year-old age group represented 26.97% ( $n=82$ ) of the respondents, suggesting a notable proportion of senior academic staff members nearing retirement age. The 18- to 29-year-old age group, which typically represents early-career academics (lecturers and junior lecturers), accounted for 10.86% ( $n = 33$ ) of the sample, indicating that a smaller but still significant proportion of younger staff members participated in the survey. Moreover, the 60 and above age group made up the smallest proportion of respondents, comprising only 5.59% ( $n = 17$ ) of the total sample. This suggests that older academics, particularly those in the late-career phase, were underrepresented in the sample. These findings are contrary to the findings reported by Sebola (2023), whose study found that there is high prevalence of older academic staff within the South African Higher Education sector.

#### 4.2.2 Gender

The gender distribution of the respondents reveals a nearly balanced representation between male and female academic staff members. Of the total sample, 49.34% ( $n = 150$ ) identified as male, while 50.66% ( $n = 151$ ) identified as female. This close proportion indicates a relatively equitable gender composition among the academic

staff at the selected higher education institution. This suggests that both male and female academics are equally represented in the study.

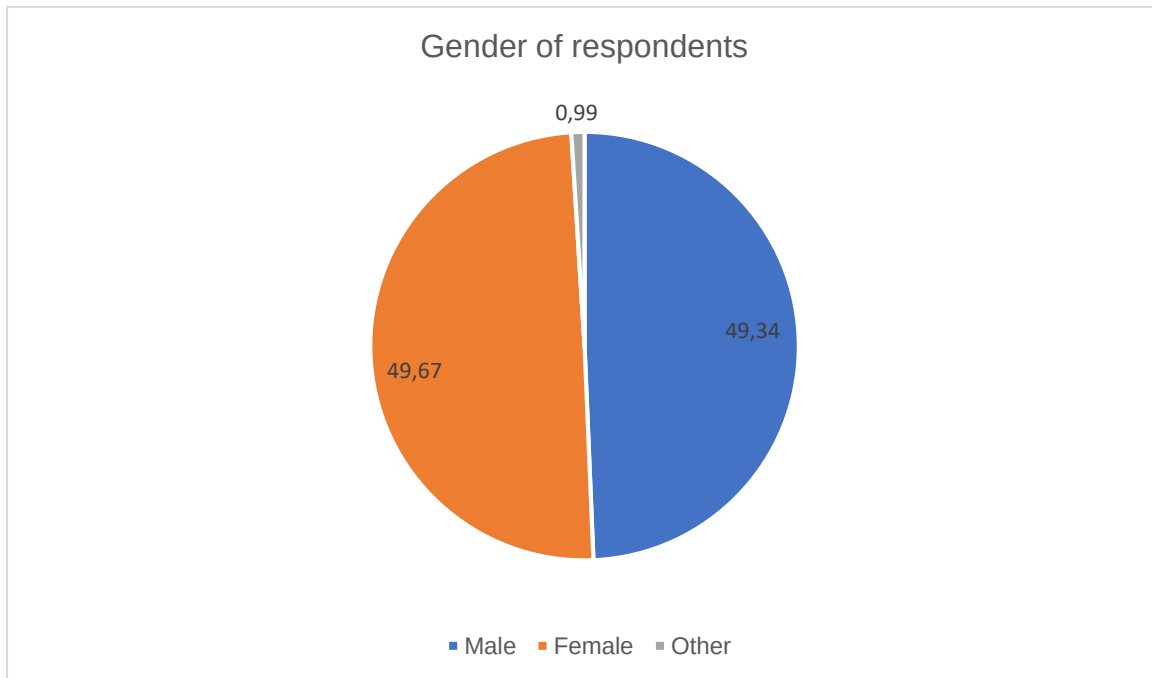


**Figure 4.2: Gender of respondents**

In addition, a small proportion of respondents, 0.99% ( $n=3$ ), identified as "Other," reflecting a minimal representation of non-binary or gender-diverse individuals within the sample. While this group is small, their inclusion highlights the study's attention to gender diversity, albeit at a limited scale. The findings of this study corroborate the study of Mkhize (2023), who reported a rise among female academics in South African HEIs.

#### 4.2.3 University Campus

The respondents in this study were distributed across several higher-education institution campuses, reflecting the academic staff's diverse geographical and operational spread. The largest group of respondents was based at the Pretoria Campus, which accounted for 24.34% ( $n=74$ ) of the total sample. This suggests that the Pretoria Campus likely represents a central hub within the institution, with a significant proportion of academic staff members located there. Furthermore, the campus is a homage to the two faculties: management sciences and engineering faculties. Figure 4.3 presents the campus distribution of the respondents.

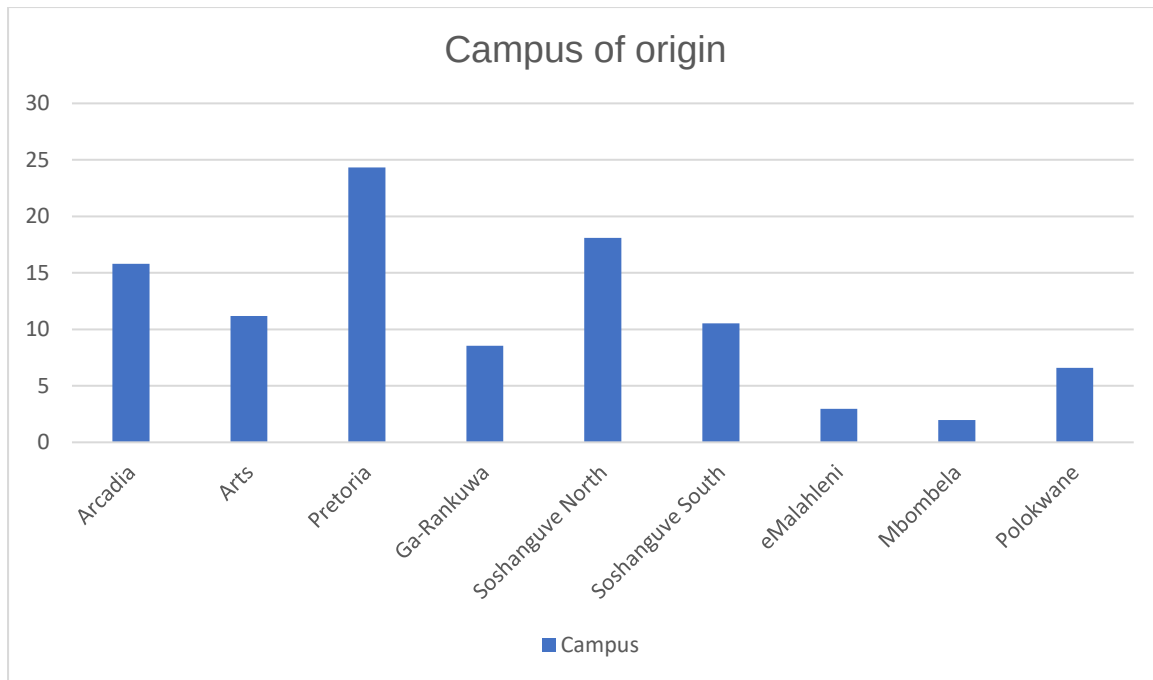


**Figure 4.3: Campus distribution of respondents**

Following Pretoria, the Arcadia Campus had the second-largest representation, with 15.79% (n=48) of the respondents. This indicates a notable presence of academic staff at this campus as well. The Soshanguve North Campus had 18.09% (n=55) of respondents, making it another key site for data collection, while the Arts Campus and Soshanguve South Campus accounted for 11.18% (n=34) and 10.53% (n=32), respectively. Together, these campuses contribute a significant portion of the overall sample (almost 30%). In contrast, the Ga-Rankuwa Campus had 8.55% (n=26) of respondents, and the Polokwane Campus had 6.58% (n =20). These figures suggest a somewhat smaller representation of academic staff from these campuses than from others. The remaining campuses had relatively smaller representations: eMalahleni Campus contributed 2.96% (n=9), while Mbombela Campus had 1.97% (n=6). These lower percentages are likely due to the smaller academic staff base or other contextual factors at these campuses.

#### 4.2.4 Job level distribution of respondents

The distribution of respondents by job level reveals a diverse range of academic staff, with most respondents holding mid-level academic positions. The Lecturer category represented the largest group, comprising 45.07% (n=137) of the respondents. This

suggests that a significant proportion of the academic staff are in the early to mid-career stages and actively engaged in teaching and research responsibilities. The distribution of the respondents' job levels is depicted in Figure 4.4.

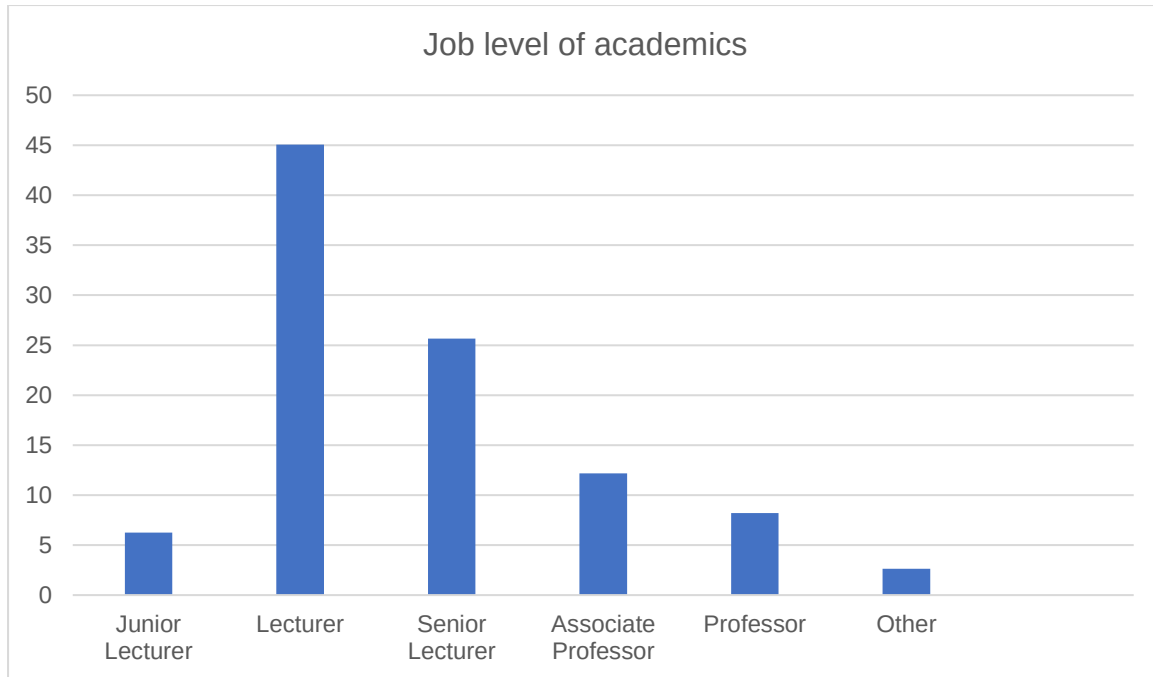


**Figure 4.4: Job level distribution**

The Senior Lecturer group, which accounted for 25.66% (n=78) of the respondents, also made up a substantial portion of the sample, indicating that a quarter of the respondents are in more experienced academic roles, likely with additional responsibilities such as supervision and involvement in departmental or faculty management. However, the Associate Professor category only represented 12.17% (n=37) of the respondents, and the Professor group comprised 8.22% (n=25) of the respondents.

These findings reflect the intricate, imbalanced roles within the South African educational space wherein senior academic represents a small population when compared to junior academic staff. According to Zulu (2021), there is a struggle among academics in South Africa, particularly women, in attaining professorship positions. The findings also revealed a significantly small sample of academics in the Junior Lecturer position, accounting for 6.25% (n=19). Mahoko (2023) asserts that factors such as low salary, conditions of service and poor recruitment contribute to the low

figures of Junior Lecturers within South African HEIs. As such, fewer early-career academics participated in the study. Moreover, the Other category, which accounted for 2.63% (n=8), likely represents respondents whose job titles do not fit neatly into the predefined categories. While small, this group adds diversity to the sample and may represent individuals in non-traditional academic roles.

#### 4.2.5 Faculty distribution of the respondents

As stated in the preceding Chapter, the institution under investigation comprises 8 faculties. The findings of this study reveal a broad representation within the academic disciplines offered. The majority of the respondents emanate from the Faculty of Management Sciences, with a sample of 23.03% (n=70). This highlights the role that this faculty plays within the institution and the programmes offered therein. The Faculty of Humanities had 18.09% (n=55) of the respondents. This suggests a strong representation of the humanities disciplines within the institution, which are typically broad and encompass teaching, policing, research, and social sciences related courses. Figure 4.5 shows the faculty distribution of the respondents.

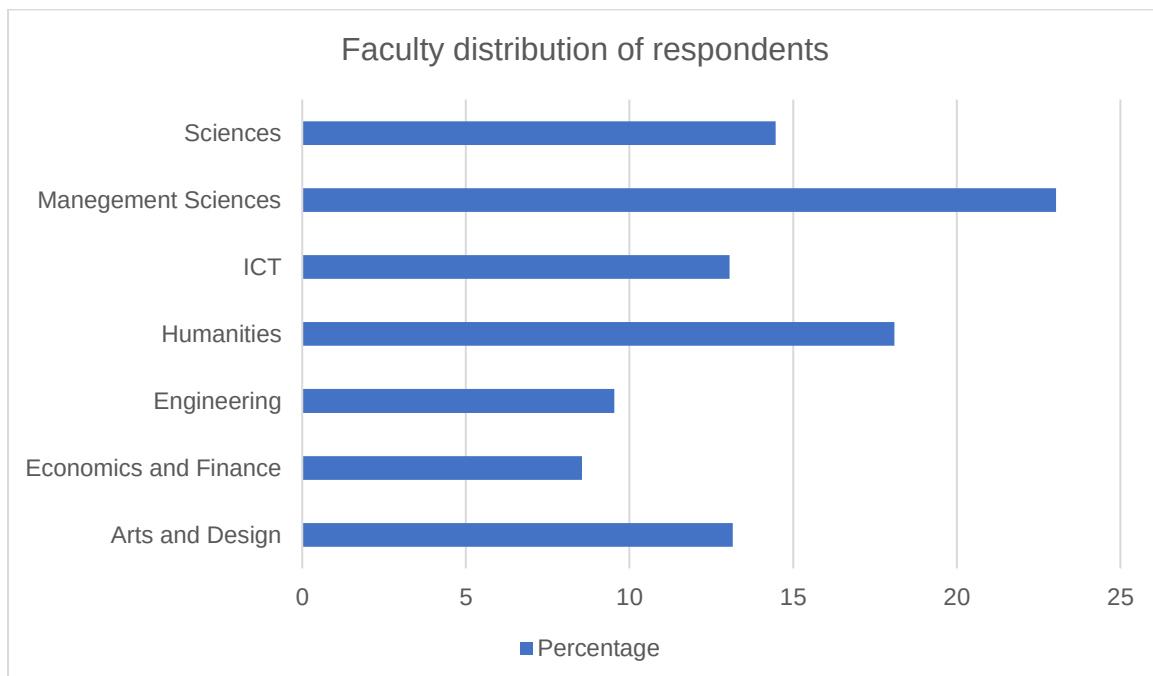


**Figure 4.5: Faculty distribution of the respondents**

The Arts and Design and Information and Communication Technology (ICT) faculties each had 13.16% (n=40) of respondents. These faculties appear to be equally represented in the sample, reflecting a balanced engagement from the creative and technical fields within the institution. The Science Faculty accounted for 14.47% (n = 44) of respondents, representing relatively strong participation from the natural and physical sciences disciplines. This is followed by the Engineering and Built Environment faculty, which had 9.54% (n = 29) respondents. While this is a smaller percentage than other faculties, it still indicates significant participation from these highly technical and research-driven disciplines. The Economics and Finance faculty had the smallest representation, accounting for 8.55% (n = 26) of the respondents. Despite being a key area within the institution, this faculty was underrepresented relative to others due to factors such as its small size and the uneven distribution of academic staff within this field, resulting from the limited programs offered by this faculty.

### 4.3 DESCRIPTIVE STATISTICS

In this section, we present the descriptive analysis of the variables relating to the respondents under study. The primary objective of this research is to develop a framework to assess the influence of technostress (TS) on the individual work performance (IWP) of academic staff at a higher education institution in South Africa. The study also assesses the moderating roles of technology self-efficacy (TSE) and Proactive Personality (PP) in this primary relationship. The dimensions of TS and IWP were assessed in the proposed conceptual framework for an empirical analysis. Furthermore, we integrated the two proposed moderators (TSE and PP) into the proposed framework. The results provide insight into the mean scores of the four core variables examined in this study: technostress, IWP (comprising task performance (TP), contextual performance (CP), and counterproductive work behaviour (CWB)), TSE, and PP. Table 4.1 outlines the abbreviations of the dimensions and constructs of the variables under study.

**Table 4.1:** List of abbreviations of dimensions and constructs

| Dimension    | Abbreviation | Variable type |
|--------------|--------------|---------------|
| Technostress | TS           | Independent   |

|                                                                                                                                                                                |                        |           |
|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|------------------------|-----------|
| Individual Work Performance <ul style="list-style-type: none"> <li>• Task Performance</li> <li>• Contextual Performance</li> <li>• Counterproductive Work Behaviour</li> </ul> | IWP<br>TP<br>CP<br>CWB | Dependent |
| Technology Self-efficacy                                                                                                                                                       | TSE                    | Moderator |
| Proactive Personality                                                                                                                                                          | PP                     | Moderator |

The following section presents the mean scores and standard deviations of the dimensions and sub-constructs of each construct. To facilitate the interpretation of the descriptive statistics, the researcher adopts a calibration approach, using a mean score threshold of 2.60 as the baseline. A mean score below 2.60 indicates respondents disagreed with the statement, while a mean score equal to or greater than 2.60 signifies agreement. In essence, a mean score within the range of 1.00 to 1.80 is associated with “strongly disagree”, 1.81 to 2.60 reflects “disagree”, 2.61 to 3.40 denotes “agree”, and 3.41 and above corresponds to “strongly agree”. Additionally, the standard deviation provides insight into the variability of responses, with values closer to zero indicating greater consensus among participants, while higher standard deviations suggest more diverse opinions. This calibration ensures a structured and meaningful interpretation of the mean scores, enabling a clearer understanding of participants’ perceptions of technostress’ influence on work performance.

#### 4.3.1 Technostress

Technostress refers to the stress experienced by individuals due to the use of Information and Communication Technologies (ICTs) (Tarafdar, 2019). In the context of this study, technostress refers to the stress experienced by academic staff resulting from the use of technology for teaching and learning purposes. Technostress was measured through twenty-three items, as reflected in the statements TS1 to TS23 in Table 4.2. The respondents were asked to rate several statements that could influence the formation of technostress due to technology adoptions and usage during their teaching endeavours. As discussed in the literature chapter, technostress is exacerbated specific technological stressors such as work overload, insecurity, and complexity in using technological tools (Chen, 2015; Ragu-Nathan *et al.*, 2008). The

instrument comprised 23 variables (5 sub-constructs), which were assessed on a 5-point Likert scale, where 1 represented "Strongly Disagree" and 5 represented "Strongly Agree." The respondents were asked to rate how these variables affected their use of technology in teaching. The mean and standard deviation scores relating to the technostress items are summarised in Table 4.2.

**Table 4.2: Means and Standard deviation scores for Technostress**

| Item statements                                                                                       | N   | MD     | SD     | Min | Max |
|-------------------------------------------------------------------------------------------------------|-----|--------|--------|-----|-----|
| <b>TS1</b> - I am forced by this technology to work much faster                                       | 304 | 4.0987 | 0.9388 | 1   | 5   |
| <b>TS2</b> - I am forced by this technology to do more work than I can handle                         | 304 | 3.9079 | 1.0521 | 1   | 5   |
| <b>TS3</b> - I am forced by this technology to work with very tight time schedules.                   | 304 | 4.0000 | 0.9749 | 1   | 5   |
| <b>TS4</b> - I am forced to change my work habits to adapt to new technologies.                       | 304 | 4.0987 | 0.8956 | 1   | 5   |
| <b>TS5</b> - I have a higher workload because of increased technology complexity.                     | 304 | 3.9770 | 1.0063 | 1   | 5   |
| <b>TS6</b> - I spend less time with my family due to this technology.                                 | 304 | 3.7270 | 1.2082 | 1   | 5   |
| <b>TS7</b> - I have to be in touch with my work even during my vacation due to this technology.       | 304 | 3.7105 | 1.2275 | 1   | 5   |
| <b>TS8</b> - I have to sacrifice my vacation and weekend time to keep current on new technologies.    | 304 | 3.4145 | 1.2662 | 1   | 5   |
| <b>TS9</b> - I feel my personal life is being invaded by this technology.                             | 304 | 3.7566 | 1.1080 | 1   | 5   |
| <b>TS10</b> - I do not know enough about this technology to handle my job satisfactorily.             | 304 | 3.2632 | 1.2599 | 1   | 5   |
| <b>TS11</b> - I need a long time to understand and use new technologies                               | 304 | 3.3783 | 1.1906 | 1   | 5   |
| <b>TS12</b> - I do not have enough time to study and upgrade my technology skills.                    | 304 | 3.6250 | 1.1188 | 1   | 5   |
| <b>TS13</b> - I find new employees to this organisation know more about computer technology than I do | 304 | 3.4836 | 1.1517 | 1   | 5   |
| <b>TS14</b> - I often find it too complex for me to understand and use new technologies.              | 304 | 3.3914 | 1.2056 | 1   | 5   |
| <b>TS15</b> - I feel constant threat to my job security due to new technologies.                      | 304 | 3.2566 | 1.2923 | 1   | 5   |
| <b>TS16</b> - I have to constantly update my technology skills to avoid being replaced.               | 304 | 3.8454 | 1.0240 | 1   | 5   |
| <b>TS17</b> - I am threatened by co-workers with newer technology skills.                             | 304 | 3.0362 | 1.2276 | 1   | 5   |
| <b>TS18</b> - I do not share my knowledge with my co-workers for fear of being replaced.              | 304 | 2.6546 | 1.2197 | 1   | 5   |
| <b>TS19</b> - I feel there is less sharing of knowledge among co-workers for fear of being replaced.  | 304 | 3.0329 | 1.2370 | 1   | 5   |
| <b>TS20</b> - There are always new developments in the technologies we use in our organisation.       | 304 | 4.4276 | 0.6459 | 2   | 5   |
| <b>TS21</b> - There are constant changes in computer software in our organisation.                    | 304 | 4.1908 | 0.8021 | 1   | 5   |
| <b>TS22</b> - There are constant changes in computer hardware in our organisation.                    | 304 | 3.8849 | 1.0514 | 1   | 5   |
| <b>TS23</b> - There are frequent upgrades in computer networks in our organisation.                   | 304 | 3.9507 | 0.9888 | 1   | 5   |

The mean scores of the technostress scale (TS1–TS23) range from 2.65 (TS18) to 4.43 (TS20) on a five-point scale, with higher mean score values indicating more significant experiences of technostress among the academic staff members. The highest-scoring items (for example, TS20:  $M = 4.43$ ,  $SD = 0.65$ ; TS21:  $M = 4.19$ ,  $SD = 0.80$ ) indicate that academic staff members frequently experience stress related to

the use of specific technologies for teaching and educational purposes. Conversely, the lower mean scores (for instance, TS18:  $M = 2.65$ ,  $SD = 1.22$ ; TS17:  $M = 3.04$ ,  $SD = 1.23$ ) imply that some aspects of technostress are less pervasive among the academics under study. The variation in responses, with standard deviations ranging from 0.65 to 1.30, highlights differences in how academic staff perceive and experience technostress.

### **4.3.2 Individual Work Performance**

The Individual Work Performance (IWP) questionnaire reflects on academics' work-related behaviours and actions relevant to the university's goals over the past three months. The respondents were asked to rate their level of agreement with the provided statements using the specified scale. The IWP scale is a second-order formative construct consisting of three first-order reflective constructs: contextual performance, task performance, and counterproductive work behaviour (Koopman *et al.*, 2014). The Likert scale for Task Performance (CP) and Contextual Performance (CP) ranges from 1 (Never) to 5 (Always), indicating how often the respondent engages in the specific work behaviour. For Counterproductive Work Behaviour (CWB), the scale ranges from 1 (Never) to 5 (Always), indicating the frequency of engaging in behaviour detrimental to organisational goals.

#### **4.3.2.1 Task performance**

Task performance (TP) encompasses an employee's core job duties and responsibilities (Carlos & Rodrigues, 2016). In the context of this study, TP includes the specific tasks, duties, and responsibilities outlined in the academics' job description (Carlos & Rodrigues, 2016). The respondents were asked to indicate their level of agreement with five statements relating to TP (i.e. TP1 to TP5), as indicated in Table 4.3. The TP subscale indicates high mean scores, ranging from 4.05 (TP5) to 4.48 (TP1), suggesting that academic staff generally perceive themselves as performing well in their core responsibilities.

**Table 4.3: Mean scores and standard deviation of TP**

| Item Statements                                                               | n   | MD     | SD     | Min | Max |
|-------------------------------------------------------------------------------|-----|--------|--------|-----|-----|
| <b>TP1</b> - I managed to plan my work so that it was done on time.           | 304 | 4.4836 | 0.6987 | 2   | 5   |
| <b>TP2</b> - My planning was optimal.                                         | 304 | 4.2632 | 0.7058 | 1   | 5   |
| <b>TP3</b> - I kept in mind the results that I had to achieve in my work.     | 304 | 4.2500 | 0.6675 | 1   | 5   |
| <b>TP4</b> - I was able to separate main issues from side issues at work.     | 304 | 4.1020 | 0.7574 | 1   | 5   |
| <b>TP5</b> - I was able to perform my work well with minimal time and effort. | 304 | 4.0559 | 0.7878 | 2   | 5   |

#### 4.3.2.2 Contextual performance

As indicated earlier, the second subscale used to measure IWP is contextual performance (CP). CP is a first-order reflective construct, which refers to the extra-role or discretionary behaviours an employee engages in beyond their formal job requirements (Koopmans, 2011:861). Notably, the CP subscale exhibits moderate-to-high mean scores ( $M = 3.82$  to  $4.23$ ), indicating that staff members actively engage in supportive, discretionary behaviours that contribute to the organisational environment (i.e. the teaching and learning environment) (See **Table 4.4**).

**Table 4.4: Mean scores and standard deviation of CP**

| Item                                                                     | n   | MD     | SD     | Min | Max |
|--------------------------------------------------------------------------|-----|--------|--------|-----|-----|
| <b>CP1</b> - I took on extra responsibilities.                           | 304 | 3.9408 | 0.9315 | 1   | 5   |
| <b>CP2</b> - I started new tasks myself, when my old ones were finished. | 304 | 3.8553 | 0.9040 | 1   | 5   |
| <b>CP3</b> - I took on challenging work tasks when available.            | 304 | 3.9046 | 0.9051 | 1   | 5   |
| <b>CP4</b> - I worked at keeping my job knowledge up-to-date.            | 304 | 4.0658 | 0.7849 | 2   | 5   |
| <b>CP5</b> - I worked at keeping my job skills up-to-date.               | 304 | 4.1020 | 0.7574 | 1   | 5   |
| <b>CP6</b> - I came up with creative solutions to new problems.          | 304 | 3.9211 | 0.7962 | 1   | 5   |
| <b>CP7</b> - I kept looking for new challenges in my job.                | 304 | 3.8224 | 0.9722 | 1   | 5   |
| <b>CP8</b> - I actively participated in work meetings.                   | 304 | 4.2368 | 0.7423 | 2   | 5   |

The results for the Contextual Performance (CP1 to CP8) demonstrate a strong commitment among academics to engage in behaviours that extend beyond their formal job requirements. For instance, 46% of respondents indicated that they usually take on extra responsibilities, with 29% always doing so, reflecting a proactive approach to their roles. Similarly, half of the respondents reported that they usually start new tasks when previous ones are finished, while 22% always take this initiative, highlighting a continuous workflow mindset. Regarding taking on challenging work,

49% indicated that they usually embrace such tasks, with 26% always doing so, which showcases academics' readiness to accept challenging responsibilities. This tendency is further reinforced by the 50% of respondents who usually work to keep their job knowledge updated and 30% who always do, emphasising their commitment to professional development.

#### 4.3.2.3 Counterproductive Work Behaviour

The third subscale used to measure IWP in this study is counterproductive work behaviour (CWB). According to Koopmans *et al.* (2011), CWB is the third and last first-order reflective subscale that assesses IWP. CWB encompasses actions or behaviours that staff members exhibit that are detrimental to the organisation (Fox, Spector, Goh, Bruursema, and Kessler, 2012:200). **Table 4.5** depicts the mean scores and the standard deviations for CWB.

**Table 4.5: Mean scores and standard deviation of CWB**

| Item                                                                                                    | n   | MD     | SD     | Min | Max |
|---------------------------------------------------------------------------------------------------------|-----|--------|--------|-----|-----|
| <b>CWB1</b> - I complained about unimportant matters at work.                                           | 304 | 2.9112 | 1.2542 | 1   | 5   |
| <b>CWB2</b> - I made problems greater than they were at work                                            | 304 | 2.6250 | 1.2836 | 1   | 5   |
| <b>CWB3</b> - I focused on the negative aspects of a work situation instead of on the positive aspects. | 304 | 2.6151 | 1.2560 | 1   | 5   |
| <b>CWB4</b> - I spoke with colleagues about the negative aspects of my work.                            | 304 | 3.2105 | 1.1696 | 1   | 5   |
| <b>CWB5</b> - I spoke with people from outside the organisation about the negative aspects of my work.  | 304 | 3.3454 | 1.3034 | 1   | 5   |

Respondents were asked to indicate their level of agreement with five statements concerning any behaviour that harms the organisation or its members. However, the CWB subscale presents lower mean scores ( $M = 2.61$  to  $3.34$ ), with CWB3 ( $M = 2.61$ ,  $SD = 1.25$ ) and CWB2 ( $M = 2.62$ ,  $SD = 1.28$ ) demonstrating the lowest values. This suggests that counterproductive behaviours, such as inefficiency or resistance to technology, are not prevalent among academic staff. CWB5 ( $M = 3.34$ ,  $SD = 1.30$ ) records the highest mean, indicating some counterproductive tendencies in specific contexts.

#### 4.3.4 Technology Self-Efficacy

Technology Self-Efficacy (TSE) relates to an individual's beliefs about their ability to succeed at specific tasks that involve the use of technology (Shu, Tu, & Wang, 2011). In an academic context, particularly for lecturers, TSE refers to the academics' belief in their ability to use technology to enhance teaching and learning effectively. In this study, respondents were asked to rate themselves on a 6-point Likert scale, ranging from 1 (Not at All) to 6 (A Great Deal), about how actively they use technology to support their pedagogical endeavours. **Table 4.6** presents a summary of means and standard deviation scores.

**Table 4.6: Mean scores and standard deviation of TSE**

| Items Statements                                                                                                                                               | N   | MD     | SD     | Min | Max |
|----------------------------------------------------------------------------------------------------------------------------------------------------------------|-----|--------|--------|-----|-----|
| <b>TSE1</b> - How competent do you perceive yourself in selecting and using various media to support teaching and learning?                                    | 304 | 5.3849 | 0.7707 | 2   | 6   |
| <b>TSE2</b> - How well prepared are you to evaluate software to support teaching and learning?                                                                 | 304 | 5.0888 | 0.8494 | 2   | 6   |
| <b>TSE3</b> - To what extent can you integrate technology across the curriculum?                                                                               | 304 | 5.0559 | 0.8125 | 2   | 6   |
| <b>TSE4</b> - How capable are you of determining why, when and how to use technology in education?                                                             | 304 | 5.0000 | 0.8482 | 3   | 6   |
| <b>TSE5</b> - To what extent do you feel prepared to select and utilise assistive technologies?                                                                | 304 | 4.8289 | 0.9176 | 2   | 6   |
| <b>TSE6</b> - To what extent did you incorporate technology to enhance teaching and learning in the lessons you taught in your field experience this semester? | 304 | 4.7862 | 0.8883 | 3   | 6   |

The TSE scale (TSE1–TSE6) was measured on a six-point scale, with mean scores ranging from 4.78 (TSE6) to 5.38 (TSE1). The consistently high means across all items suggest that academic staff generally exhibit strong confidence in navigating and effectively using technological tools in their professional academic activities. This high level of self-efficacy is crucial, as previous research suggests that individuals with greater technological confidence are more likely to adapt. The analysis of TSE provides insight into individuals' confidence in their abilities to utilise technology effectively in various educational contexts.

#### 4.3.5 Proactive Personality

Proactive Personality refers to a personality trait that is characterised by individuals who demonstrate openness to experience and conscientiousness, which can enhance job performance (Alikaj, Ning & Wu, 2021). The respondents were asked to rate themselves using the provided 7-point Likert scale, typically ranging from “Strongly Disagree” to “Strongly Agree”, for each statement based on how well it described their experiences and beliefs in influencing their surroundings. In an academic context, a PP fosters initiative, adaptability, and collaboration, leading to enhanced performance, a positive work environment, and improved educational outcomes for both academics and students. **Table 4.7** summarises the findings of the proactivity behaviour of the respondents under study.

**Table 4.7: Mean scores and standard deviation of PPS**

| Items Statement                                                                               | n   | MD     | SD     | Min | Max |
|-----------------------------------------------------------------------------------------------|-----|--------|--------|-----|-----|
| <b>PPS1</b> - I am constantly on the lookout for new ways to improve my life.                 | 304 | 6.1053 | 0.7097 | 2   | 7   |
| <b>PPS2</b> - I feel driven to make a difference in my community and maybe the world.         | 304 | 5.9243 | 0.8812 | 1   | 7   |
| <b>PPS3</b> - I tend to let others take the initiative to start new projects. (Reverse coded) | 304 | 5.4572 | 1.1738 | 1   | 7   |
| <b>PPS4</b> - Wherever I have been, I have been a powerful force for constructive change.     | 304 | 5.5428 | 1.0040 | 2   | 7   |
| <b>PPS5</b> - I enjoy facing and overcoming obstacles to my ideas.                            | 304 | 5.5625 | 0.9524 | 1   | 7   |
| <b>PPS6</b> - Nothing is more exciting than seeing my ideas turn into reality.                | 304 | 5.7632 | 0.9280 | 3   | 7   |
| <b>PPS7</b> - If I see something I don't like, I fix it.                                      | 304 | 5.1513 | 1.2936 | 1   | 7   |
| <b>PPS8</b> - No matter what the odds, if I believe in something, I will make it happen.      | 304 | 5.4145 | 1.1195 | 1   | 7   |
| <b>PPS9</b> - I love being a champion for my ideas, even against others' opposition.          | 304 | 5.4901 | 1.1198 | 1   | 7   |
| <b>PPS10</b> - I excel at identifying opportunities.                                          | 304 | 5.0625 | 1.3928 | 1   | 7   |
| <b>PPS11</b> - I am always looking for better ways to do things.                              | 304 | 5.4013 | 1.1418 | 1   | 7   |
| <b>PPS12</b> - If I believe in an idea, no obstacle will prevent me from making it happen.    | 304 | 5.4243 | 0.9988 | 2   | 7   |
| <b>PPS13</b> - I love to challenge the status quo.                                            | 304 | 4.6809 | 1.5544 | 1   | 7   |
| <b>PPS14</b> - When I have a problem, I tackle it head-on.                                    | 304 | 5.1546 | 1.2237 | 1   | 7   |
| <b>PPS15</b> - I am great at turning problems into opportunities.                             | 304 | 5.2895 | 1.0694 | 2   | 7   |
| <b>PPS16</b> - I can spot a good opportunity long before others can.                          | 304 | 5.3980 | 1.0481 | 2   | 7   |
| <b>PPS17</b> - If I see someone in trouble, I help out in any way I can.                      | 304 | 5.7303 | 0.8748 | 2   | 7   |

As indicated, the Proactive Personality Scale (PPS1–PPS18) was assessed on a seven-point Likert scale, with mean scores ranging from 4.68 (PPS13) to 6.10 (PPS1),

as shown in Table 4.6. The results indicate that academic staff generally exhibit a high degree of proactivity, with several items exceeding a mean of 5.5, suggesting that most respondents actively take the initiative and engage in self-directed efforts to improve their use of technology for pedagogical reasons. However, PPS13 ( $M = 4.68$ ,  $SD = 1.55$ ) records a relatively lower score, suggesting that certain aspects of proactivity, such as initiating long-term strategic actions, may be less prevalent among some individual academic staff members. Table 4.8 presents the mean scores and standard deviations for TS, IWP, TSE, and PP.

**Table 4.8: Means and Standard Deviations for Factors and Scales**

| Factor/Scale                                    | Mean (M) | Standard Deviation (SD) |
|-------------------------------------------------|----------|-------------------------|
| Technostress (TS - Total Scale)                 | 3.68     | 1.08                    |
| Technostress Subscales                          |          |                         |
| Techno-Overload (TS1 - TS5)                     | 4.02     | 0.97                    |
| Techno-Complexity (TS6 - TS10)                  | 3.63     | 1.10                    |
| Techno-Insecurity (TS11 - TS15)                 | 3.43     | 1.18                    |
| Techno-Uncertainty (TS16 - TS20)                | 3.60     | 1.04                    |
| Individual Work Performance (IWP - Total Scale) | 4.22     | 0.74                    |
| Individual Work Performance Subscales           |          |                         |
| Task Performance (TP1 - TP5)                    | 4.23     | 0.74                    |
| Counterproductive Work Behavior (CWB1 - CWB5)   | 2.99     | 1.26                    |
| Technological Self-Efficacy (SE - Total Scale)  | 4.60     | -                       |
| Proactive Personality (PPS - Total Scale)       | 5.39     | 1.08                    |
| Proactive Personality Subscales                 |          |                         |
| Initiative (PPS1 - PPS6)                        | 5.69     | 0.96                    |
| Perseverance (PPS7 - PPS12)                     | 5.37     | 1.14                    |
| Problem-Solving (PPS13 - PPS18)                 | 4.93     | 1.24                    |

Technostress ( $M = 3.68$ ,  $SD = 1.08$ ) exhibits moderate levels across participants. Techno-overload ( $M = 4.02$ ,  $SD = 0.97$ ) is the most pronounced stressor, indicating that increased workload and the pressure of adapting to technology have a significant impact on employees. Techno-Complexity ( $M = 3.63$ ,  $SD = 1.10$ ) and Techno-Uncertainty ( $M = 3.60$ ,  $SD = 1.04$ ) also contribute to the overall stress, while Techno-Insecurity ( $M = 3.43$ ,  $SD = 1.18$ ) is slightly lower, indicating moderate concerns about job stability due to technological advancements.

Individual Work Performance (IWP) ( $M = 4.22$ ,  $SD = 0.74$ ) is relatively high, suggesting that employees generally perform well in their tasks. Task Performance ( $M = 4.23$ ,  $SD = 0.74$ ) is significantly higher than Counterproductive Work Behavior (CWB) ( $M = 2.99$ ,

SD = 1.26), indicating that while some employees engage in negative workplace behaviours, overall performance remains high.

In the current dataset, the mean scores across all six TSE items range from 4.78 (TSE6) to 5.38 (TSE1), indicating higher technology self-efficacy among the participants. The highest-rated item, TSE1 ( $M = 5.38$ ,  $SD = 0.77$ ), measures competence in selecting and using various media for teaching, suggesting that respondents feel exceptionally skilled in identifying appropriate technological tools. The lowest-rated item, TSE6 ( $M = 4.78$ ,  $SD = 0.89$ ), pertains to the actual incorporation of technology into field experience lessons.

Proactive Personality ( $M = 5.39$ ,  $SD = 1.08$ ) is the highest-rated construct, indicating that employees tend to be highly proactive in their work approach. The highest-rated subscale is Initiative ( $M = 5.69$ ,  $SD = 0.96$ ), followed by Perseverance ( $M = 5.37$ ,  $SD = 1.14$ ) and Problem-Solving ( $M = 4.93$ ,  $SD = 1.24$ ), suggesting that employees are persistent in overcoming work-related challenges but might struggle slightly more with finding solutions.

#### **4.4 INDEPENDENT SAMPLE TESTS**

The primary objective of this section is to investigate whether there are statistically significant differences in technostress, IWP (TP, CP, CWB), TSE, and PP between male and female academic staff. To address this objective, the Kruskal-Wallis test for equality of populations' ranks was conducted. The Kruskal-Wallis test is appropriate given the ordinal nature of the likert-scale data and the potential for non-normality in the distribution of responses. However, to further assess pairwise differences between the two gender groups, the Mann-Whitney U test (also known as the Wilcoxon rank-sum test) was employed (Fay & Proschan, 2010).

The Mann-Whitney U test is a non-parametric alternative to the independent samples t-test, designed to evaluate whether two independent groups (in this case, male and female academic staff) differ significantly in their distribution of scores. Unlike parametric tests, the Mann-Whitney U test does not assume normality and is particularly useful when dealing with ordinal data or small sample sizes (Fay & Proschan, 2010). It ranks all observations and compares the sum of ranks between

the two groups rather than directly comparing means, making it robust to outliers and violations of normality assumptions.

In assessing the results of the Mann-Whitney U test, statistical significance is determined by the U statistic and the associated p-value (Fay & Proschan, 2010). A p-value below 0.05 indicates that the distributions of the two groups are significantly different, meaning that gender plays a role in influencing the studied variables. Moreover, the effect size can be calculated to determine the practical significance of the observed differences on how gender may influence technostress, performance, and personality traits among academic staff.

#### 4.4.1 Gender distribution and differences

**Table 4.9** presents the gender distribution among the study respondents. Of the 304 academic staff surveyed, 49.34% (n = 150) were male, while 49.67% (n = 151) were female, indicating a near-equal representation of both genders. Additionally, 0.99% (n = 3) of the respondents identified as “Other,” contributing to the overall sample diversity.

**Table 4.9: Gender Distribution of Respondents**

| Gender       | Frequency  | Percentage (%) | Cumulative (%) |
|--------------|------------|----------------|----------------|
| Male         | 150        | 49.34          | 49.34          |
| Female       | 151        | 49.67          | 99.01          |
| Other        | 3          | 0.99           | 100.00         |
| <b>Total</b> | <b>304</b> | <b>100.00</b>  | <b>-</b>       |

The balanced distribution of male and female participants ensures that gender-based comparisons in the subsequent analysis are statistically meaningful and not biased by disproportionate representation. The findings provide a solid foundation for exploring gender-based differences in how technostress influences academic staff performance in higher educational institutions. Furthermore, the findings offer insights into how technology efficacy and proactivity traits could leverage this technostress-performance relationship.

#### 4.4.2 Kruskal-Wallis Test Results by Gender

**Table 4.10** presents the Kruskal-Wallis equality-of-populations rank test results, which examined whether statistically significant differences exist between male and female academic staff in terms of technostress, IWP (TP, CP, CWB), TSE and proactive personality. The analysis (see Table 4.10) reports the rank sums for male and female respondents, chi-square ( $\chi^2$ ) values, and p-values, which indicate whether the observed differences between the genders are statistically significant.

**Table 4.10: Technostress Kruskal-Wallis Test Results by Gender**

| Variable                   | Male Rank Sum | Female Rank Sum | Chi <sup>2</sup> Value | p-value | p-value (with ties) |
|----------------------------|---------------|-----------------|------------------------|---------|---------------------|
| Technostress               | 24138.50      | 21312.50        | 3.887                  | 0.0487  | 0.0472              |
| Individual Variance (Inva) | 23587.00      | 21864.00        | 1.540                  | 0.2146  | 0.2109              |
| Complacency (Compl)        | 21756.50      | 23694.50        | 1.401                  | 0.2366  | 0.2351              |
| Insecurity (Inse)          | 23055.00      | 22396.00        | 0.288                  | 0.5916  | 0.5907              |
| Uncertainty (Uncert)       | 22935.00      | 22516.00        | 0.143                  | 0.7058  | 0.7033              |

Notably, the results indicate a statistically significant difference in technostress levels between male and female academic staff ( $\chi^2 = 3.887$ ,  $p = 0.0487$ ), suggesting that gender may play a role in how technostress is experienced in the higher education workplace. However, for other variables such as individual variance, complacency, techno-insecurity, techno-uncertainty, task performance, contextual performance, counterproductive work behaviour, technology self-efficacy, and proactive personality, no statistically significant differences were found ( $p > 0.05$ ), implying that both male and female respondents exhibit similar distributions for these constructs. These findings provide empirical insights into the gendered experiences of technostress and work-related attributes among academic staff, reinforcing the need to further explore gender-sensitive interventions in managing technostress and enhancing work performance, particularly within the higher education sector.

- **Technostress**

The results indicate a statistically significant difference in technostress levels between male and female academic staff ( $\chi^2 = 3.887$ ,  $p = 0.0472$ ), suggesting that gender plays

a role in the experience of technostress among academic staff. The rank sum for male participants (24,138.50) was higher than that of female participants (21,312.50), implying that male academic staff members report higher levels of technostress (see Table 4.9. This finding may indicate that male staff experience more significant challenges adapting to technological demands or perceive a higher degree of digital workload.

- **Individual Work Performance**

As discussed earlier, the IWP construct comprises three sub-constructs (TP, CP and CWB). **Table 4.11** below presents the summarised Kruskal-Wallis test results for the IWP sub-constructs by gender.

**Table 4.11: IWP Kruskal-Wallis Test Results by Gender**

| Variable                               | Male Rank Sum | Female Rank Sum | Chi <sup>2</sup> Value | p-value | p-value (with ties) |
|----------------------------------------|---------------|-----------------|------------------------|---------|---------------------|
| Task Performance (TP)                  | 22373.00      | 23078.00        | 0.135                  | 0.7137  | 0.7089              |
| Contextual Performance (CP)            | 22875.50      | 22575.50        | 0.089                  | 0.7651  | 0.7644              |
| Counterproductive Work Behaviour (CWB) | 23602.00      | 21849.00        | 1.590                  | 0.2073  | 0.2063              |

The results for TP ( $\chi^2 = 0.139$ ,  $p = 0.7089$ ) and CP ( $\chi^2 = 0.090$ ,  $p = 0.7644$ ) suggest that there are no significant gender differences. This indicates that both male and female academic staff demonstrate similar levels of effectiveness in their core responsibilities and their discretionary contributions to the organisational environment concerning work performance.

Regarding CWB ( $\chi^2 = 1.597$ ,  $p = 0.2063$ ), the absence of a statistically significant difference suggests that both genders exhibit comparable levels of negative work behaviours, such as resistance to technological changes or inefficiency due to the presence of digital stressors. While the rank sum for male staff (23,602.00) was higher than that of female staff (21,849.00), the observed differences are not statistically meaningful.

- **Technology Self-Efficacy**

**Table 4.12** summarises the Kruskal-Wallis test results for the moderating variable of this study (i.e. TSE).

**Table 4.12: TSE Kruskal-Wallis Test Results by Gender**

| Variable                  |       | Male Sum | Rank | Female Sum | Rank | Chi <sup>2</sup> Value | p-value | p-value (with ties) |
|---------------------------|-------|----------|------|------------|------|------------------------|---------|---------------------|
| Technology Efficacy (TSE) | Self- | 23028.50 |      | 22422.50   |      | 0.251                  | 0.6161  | 0.6142              |

The Kruskal-Wallis test for TSE ( $\chi^2 = 0.254$ ,  $p = 0.6142$ ) indicates no significant gender differences, suggesting that both male and female academic staff report similar confidence levels in using technology effectively for academic purposes. This aligns with existing research suggesting that when provided with equal exposure to digital tools, individuals develop comparable levels of technological competence, irrespective of gender.

- **Proactive Personality**

Table 4.13 presents the Kruskal-Wallis test results for the second moderator of this study (i.e., proactive personality).

**Table 4.13: Proactive Personality Kruskal-Wallis test results by gender**

| Variable                   |             | Male Sum | Rank | Female Sum | Rank | Chi <sup>2</sup> Value | p-value | p-value (with ties) |
|----------------------------|-------------|----------|------|------------|------|------------------------|---------|---------------------|
| Proactive Personality (PP) | Personality | 21737.00 |      | 23714.00   |      | 1.462                  | 0.2266  | 0.2263              |

The results for proactive personality ( $\chi^2 = 1.464$ ,  $p = 0.2263$ ) similarly indicate no statistically significant differences between male and female academic staff. This suggests that both genders demonstrate comparable levels of initiative-taking and problem-solving tendencies when dealing with technological challenges and adapting to change in the workplace.

#### 4.4.2 Age differences

This section assessed whether significant differences exist in technostress, IWP (and its sub-constructs, TP, CP and CWB), TSE, and proactive personality across different age groups through the Kruskal-Wallis test approach. One of the key advantages of this analysis is that it is a non-parametric method, which is appropriate given the ordinal nature of the data collected in this study and the potential for non-normality (Ostertagova, Ostertag, & Kováč, 2014). In this study, we utilised Dunn's test (a non-parametric statistical procedure) to identify which specific groups differ from each other following a significant result from the Kruskal-Wallis test (Pohlert, 2014). The Dunn's test performs pairwise comparisons between groups to determine which pairs exhibit statistically significant differences. This test is beneficial when the assumptions of parametric tests are not met, making it a valuable tool for analysing ordinal data or data that do not follow a normal distribution, such as the case in this study (Pohlert, 2014).

##### 4.4.2.1 Age distribution

Table 4.14 presents the Kruskal-Wallis equality-of-populations rank test results, which were conducted to assess statistical differences across different age groups for the studied variables. The table reports rank sums for each age group, chi-square ( $\chi^2$ ) values, and p-values to determine whether there are significant differences between age groups. The distribution shows that the majority of the participants fall within the 40–49 ( $n = 88$ ) and 30–39 ( $n = 84$ ) age categories, followed by 50–59 ( $n = 82$ ). The youngest group, 18–29 years ( $n = 33$ ), and the 60 and above category ( $n = 17$ ) represent the smallest portions of the sample. This distribution provides a diverse demographic composition, ensuring a broad representation of experiences regarding the variables under study across different academic career stages.

**Table 4.14: Kruskal-Wallis Test Results by Age Group**

| Age Group    | Observations (Obs) | Rank Sum | Chi <sup>2</sup> Value | p-value | p-value (with ties) |
|--------------|--------------------|----------|------------------------|---------|---------------------|
| 18 – 29      | 33                 | 4672.00  | 5.036                  | 0.2836  | 0.2769              |
| 30 – 39      | 84                 | 11891.00 | 17.630                 | 0.0015  | 0.0013              |
| 40 – 49      | 88                 | 13157.00 | 25.876                 | 0.0001  | 0.0001              |
| 50 – 59      | 82                 | 13745.50 | 9.889                  | 0.0423  | 0.0414              |
| 60 and above | 17                 | 2894.50  | 18.041                 | 0.0012  | 0.0010              |

#### 4.4.2.2 Results of the Kruskal-Wallis Test

**Table 4.15** summarises the results of the Kruskal-Wallis equality-of-populations rank test, which examined whether statistically significant differences exist across the different age groups for the studied variables. The rank sums, chi-square ( $\chi^2$ ) values, and p-values indicate the extent to which the responses from various age groups vary.

**Table 4.15: Results of the Kruskal-Wallis rank test**

| Variable                               | $\chi^2$ (df = 4) | p-value | Significance    |
|----------------------------------------|-------------------|---------|-----------------|
| Technostress                           | 5.103             | 0.2769  | Not significant |
| Individual variance (Inva)             | 17.908            | 0.0013  | Significant     |
| Complacency (Compl)                    | 26.039            | 0.0001  | Significant     |
| Insecurity (Inse)                      | 9.940             | 0.0414  | Significant     |
| Uncertainty (Uncert)                   | 18.373            | 0.0010  | Significant     |
| Task Performance (TP)                  | 17.259            | 0.0017  | Significant     |
| Contextual Performance (CP)            | 13.891            | 0.0077  | Significant     |
| Counterproductive Work Behaviour (CWB) | 10.193            | 0.0373  | Significant     |
| Technology Self-Efficacy (TSE)         | 24.672            | 0.0001  | Significant     |
| Proactive Personality (PP)             | 10.350            | 0.0349  | Significant     |

The results reveal that significant differences exist among age groups for several variables, including individual variance ( $p = 0.0015$ ), complexity ( $p = 0.0001$ ), insecurity ( $p = 0.0423$ ), uncertainty ( $p = 0.0012$ ), task performance ( $p = 0.0022$ ), contextual performance ( $p = 0.0080$ ), counterproductive work behaviour ( $p = 0.0381$ ), technology self-efficacy ( $p = 0.0001$ ), and proactive personality ( $p = 0.0351$ ). These findings suggest that age-related variations influence how academic staff experience technostress, work performance, and personal attributes in adapting to technological demands.

The analysis further reveals that technostress does not significantly differ across age groups ( $\chi^2 = 5.103$ ,  $p = 0.2769$ ), suggesting that academic staff experience similar levels of technostress regardless of age. This finding indicates that while technostress is prevalent, it is not necessarily influenced by generational differences. However, significant differences were found for individual variance ( $p = 0.0013$ ), complacency ( $p = 0.0001$ ), insecurity ( $p = 0.0414$ ), uncertainty ( $p = 0.0010$ ), task performance ( $p = 0.0017$ ), contextual performance ( $p = 0.0077$ ), counterproductive work behaviour ( $p = 0.0373$ ), technology self-efficacy ( $p = 0.0001$ ), and proactive personality ( $p = 0.0349$ ). These results indicate that certain aspects of work performance and moderating factors, such as TSE and PP, vary significantly between age groups.

#### 4.4.2.3 Dunn's Pairwise Comparison Results (Bonferroni Adjustment)

**Table 4.16** summarises Dunn's Pairwise Comparisons performed post hoc to determine where significant differences exist between age groups for different study variables. A p-value of less than 0.05 indicates statistically significant differences between specific age groups.

**Table 4.16: Dunn's Pairwise Comparison Results (Bonferroni Adjustment)**

| Variable                               | Significant Differences Found? | p-value |
|----------------------------------------|--------------------------------|---------|
| Individual Variance (Inva)             | Yes                            | 0.0015  |
| Techno-complexity (Compl)              | Yes                            | 0.0001  |
| Techno-Insecurity (Inse)               | Yes                            | 0.0423  |
| Techno-Uncertainty (Uncert)            | Yes                            | 0.0012  |
| Task Performance (TP)                  | Yes                            | 0.0022  |
| Contextual Performance (CP)            | Yes                            | 0.0080  |
| Counterproductive Work Behaviour (CWB) | Yes                            | 0.0381  |
| Technology Self-Efficacy (TSE)         | Yes                            | 0.0001  |
| Proactive Personality (PP)             | Yes                            | 0.0351  |

Dunn's pairwise comparisons provide deeper insights into the observed differences across age groups concerning technostress, IWP, TSE, and PP. For individual variance, significant differences were identified between the 50–59 age group and younger age groups ( $p = 0.0012$ ), suggesting that older academic staff may demonstrate greater consistency in their performance. Regarding techno-complexity, the 40–49 and 50–59 age groups exhibited significantly higher complexity levels than younger age groups ( $p < 0.0023$ ), implying that older staff may struggle more with adapting to technological changes.

Regarding techno-insecurity, the 40-49 age group reported significantly different levels of insecurity than younger groups ( $p = 0.0116$ ), suggesting that mid-career academics may experience greater uncertainty regarding their technological competencies. Similarly, techno-uncertainty was significantly lower in the 30-39 age group compared to the 50-59 age group ( $p = 0.0005$ ), indicating that younger academics may feel more confident navigating digital transformations. In terms of PP, younger academics (18-29 years old) exhibited significantly lower scores than older groups ( $p = 0.0458$ ), reinforcing the notion that work experience has a positive influence on performance outcomes. A similar trend was observed for contextual performance (CP), where the 50–59 age group scored significantly higher than the 30-39 and 40-49 age groups ( $p$

= 0.0082), highlighting the importance of experience in fostering workplace collaboration and adaptability.

For CWB, the 40-49 age group demonstrated significantly higher scores than younger academics ( $p = 0.0085$ ), suggesting that mid-career academics may be more resistant to workplace expectations or organisational demands. Conversely, for TSE, the 18–29 age group reported significantly higher confidence in technology use than the 50–59 and 60+ age groups ( $p < 0.0012$ ), reinforcing the generational divide in digital fluency and technological adaptability. Lastly, for proactive personality, significant differences were found between younger and older groups ( $p < 0.0349$ ), indicating that younger academics tend to adapt more proactively to technological and organisational changes. These findings suggest that age plays a critical role in shaping perceptions of technostress, performance, and digital adaptability in academic settings.

#### 4.5 RELATIONSHIP BETWEEN TECHNOSTRESS AND INDIVIDUAL PERFORMANCE

Spearman's rank correlation coefficient ( $\rho$ ), or Spearman's rho, is a non-parametric measure of the strength and direction of association between two ranked variables (Chatterjee, 2021). Spearman's correlation coefficient is a statistical measure used to assess the strength and direction of a monotonic relationship between two variables (Al-Hameed, 2022). A strong negative correlation would indicate that higher technostress significantly reduces work performance, while a weak or negligible correlation would suggest that other factors moderate this relationship. Spearman's correlation assesses whether an increase in one variable corresponds to an increase or decrease in another (Al-Hameed, 2022). According to Dancey and Reidy (2017), the interpretation of Spearman's correlation ( $r_s$ ) follows similar conventions to Pearson's correlation but applies to ranked data rather than continuous variables. As such, the strength of association is typically classified as indicated in **Table 4.17**.

**Table 4.17: Guidelines on interpreting Spearman's correlation**

| Strength of Association | Coefficient $r$ |                |
|-------------------------|-----------------|----------------|
|                         | Positive        | Negative       |
| Small                   | 0.10 to 0.29    | -0.10 to -0.29 |
| Medium                  | 0.30 to 0.49    | -0.30 to -0.49 |

|       |             |               |
|-------|-------------|---------------|
| Large | 0.50 to 1.0 | -0.50 to -1.0 |
|-------|-------------|---------------|

Source: Dancey & Reidy (2017)

In the context of this study, which examines the relationship between technostress and work performance among academic staff, Spearman's correlation is perceived as an appropriate tool to understand the extent to which higher levels of technostress are associated with variations in work performance among academic staff. For this study, correlations are analysed in preparation for the subsequent regression analysis and also to address Research Objective 4 (i.e., to establish if there is a relationship between technostress and individual work performance).

The Spearman's correlation coefficient between the overall Technostress score and the overall IWP score is  $r = -0.85$ , with a  $p$ -value  $< 0.007$ . This indicates a very strong negative relationship between Technostress and IWP, strong evidence against the null hypothesis. The result suggests that as employees' experience of Technostress increases, their overall work performance significantly decreases.

**Table 4.18: Correlation between the primary constructs**

| Independent Variable | Dependant variable                | Correlation Coefficient (Spearman's rho) | p-value |
|----------------------|-----------------------------------|------------------------------------------|---------|
| Technostress         | Individual Work Performance (IWP) | -0.849                                   | 0.007   |

Note:  $p = p$ -value for Spearman's correlation.

The magnitude of the correlation ( $r = -0.85$ ) reflects a very strong inverse relationship in this study between Technostress and the work performance of academic staff members. This correlation highlights the critical impact of technostress on employee performance outcomes within an organisation.

Given that technostress and IWP (TP, CP, and CWB) were assessed using Likert-scale survey responses, Spearman's correlation was perceived to be appropriate for the current study (Chatterjee, 2021). May and Looney (2020) highlight the importance of proper sample size determination in correlation analysis; ensuring sufficient participants is crucial for obtaining reliable and generalisable results. A strong negative correlation would suggest that increased technostress significantly reduces work

performance, while a weak correlation would imply that other factors may influence this relationship.

This section presents the correlation analysis between the aggregated scores of the technostress dimensions and the sub-constructs of IWP. The aim is to assess the degree and direction of association between technostress factors and the three IWP outcomes: TP, CP, and CWB. Due to the non-parametric nature of the data, the correlation coefficients were calculated using Spearman's rank-order correlation. All correlations of the technostress dimensions and IWP can be seen in **Table 4.19** below.

**Table 4.19: Correlation between Technostress and IWP Constructs**

|                           | Task Performance | Contextual Performance | Counterproductive Work Behaviour |
|---------------------------|------------------|------------------------|----------------------------------|
| <b>Techno-overload</b>    | -0.62            | -0.55                  | 0.58                             |
| <b>Techno-invasion</b>    | -0.47            | -0.50                  | 0.44                             |
| <b>Techno-complexity</b>  | -0.40            | -0.38                  | 0.46                             |
| <b>Techno-insecurity</b>  | -0.35            | -0.30                  | 0.52                             |
| <b>Techno-uncertainty</b> | -0.22            | -0.28                  | 0.31                             |

*Note: Spearman's rho (r values)*

There is a strong negative correlation between Techno-overload and TP ( $r = -0.62$ ,  $p < 0.01$ ), suggesting that higher levels of overload due to technology use significantly reduce employees' ability to perform their core job tasks effectively. Techno-invasion and Techno-complexity are also moderately negatively correlated with TP ( $r = -0.47$  and  $r = -0.40$ , respectively), indicating that technology's intrusion into people's personal lives and the complexity of technology use contribute to reduced task efficiency. Techno-insecurity and Techno-uncertainty show weaker but significant negative correlations with TP ( $r = -0.35$  and  $r = -0.22$ , respectively), reflecting that fear of job loss and uncertainty related to technology adoption in the academic workspace can undermine task performance, although to a lesser degree.

A strong negative relationship is observed between Techno-overload and CP ( $r = -0.55$ ,  $p < 0.01$ ), meaning that employees experiencing technology-induced workload pressures are less likely to engage in helpful behaviours beyond their formal job requirements. Techno-invasion ( $r = -0.50$ ) and Techno-complexity ( $r = -0.38$ ) also exhibit moderate negative correlations, suggesting that work-life interference and

difficulty in using technology impede employees' willingness to go beyond their prescribed roles. Techno-insecurity and Techno-uncertainty have weaker negative correlations with CP ( $r = -0.30$  and  $r = -0.28$ , respectively).

Techno-overload shows a strong positive correlation with CWB ( $r = 0.58$ ,  $p < 0.01$ ), implying that excessive technology-driven workload may lead employees to engage in behaviours that are harmful to the organisation. Techno-insecurity ( $r = 0.52$ ) and Techno-complexity ( $r = 0.46$ ) also exhibit moderate positive correlations with CWB, indicating that job insecurity and difficulty navigating technology may contribute to counterproductive work behaviours. Techno-invasion ( $r = 0.44$ ) and Techno-uncertainty ( $r = 0.31$ ) demonstrate weaker but still significant positive correlations, indicating that both factors can also lead to negative workplace behaviour, albeit to a lesser extent.

#### **4.6 RELIABILITY OF RESEARCH INSTRUMENTS**

In this section, we analyse the reliability of the research instruments that were used to explain the influence of technostress on academic staff's performance. The section begins with the illustration of the reliability of the technostress instrument, which was achieved through the use of the Cronbach's alpha technique. The Cronbach's alpha is a well-known technique for measuring the internal consistency of an instrument to ensure reliability and thereby enhance the credibility of the research findings (Hajjar, 2018).

##### **4.6.1 Reliability statistics for the Technostress instrument**

The Technostress Instrument is designed to measure various sub-constructs of technostress, which are crucial for understanding the multifaceted nature of stress induced by technology in the workplace. The instrument consists of five subscales: techno-overload, techno-invasion, techno-complexity, techno-insecurity, and techno-uncertainty. In this study, the analysis provides an overview of the reliability statistics, including Cronbach's alpha for each sub-construct and the overall scale.

##### **Techno-overload (Items TS1-TS6)**

- Cronbach's alpha: 0.7986

- The techno-overload subscale exhibits a high level of internal consistency, as indicated by an alpha of 0.7986. Each item shows strong item-test correlations, particularly TS2 (0.7734) and TS4 (0.6384). However, TS4 shows a relatively lower correlation. This may suggest the need for refinement of this construct. The overall measurement, however, indicates that the constructs (TS1 -TS6) capture the pressures of workload and time constraints imposed by the use of technology.

#### **Techno-invasion (Items TS7-TS9)**

- Cronbach's alpha: 0.7304
- The Techno-invasion subscale demonstrates acceptable reliability, with an alpha value of 0.7304. Within this subscale, TS8 displayed the highest alpha value of 0.8784, demonstrating excellent reliability. However, the lower item-test correlation for TS9 (0.4765) suggests that the item may not align as closely with the overall construct as others.

#### **Techno-complexity (Items TS10-TS14)**

- **Cronbach's alpha:** 0.8333
- This subscale exhibits excellent internal consistency, with a Cronbach's alpha of 0.8333. All items within the techno-complexity subscale showed relatively good item-test correlations, with TS13 and TS14 displaying the highest correlations (0.7330 and 0.8039, respectively). This indicates that respondents perceived technology as complex and potential contributor to technostress formation.

#### **Techno-insecurity (Items TS15-TS19)**

- **Cronbach's alpha:** 0.7839
- The techno-insecurity subscale also shows good reliability, with an alpha of 0.7839. Item correlations indicate that TS17 (0.8289) is particularly strong, suggesting it effectively captures feelings of insecurity related to technology. Although TS16 shows a lower item-test correlation (0.5695), it still makes a positive contribution to the overall construct.

### **Techno-uncertainty (Items TS20-TS23)**

- **Cronbach's alpha:** 0.7385
- The techno-uncertainty subscale has a respectable alpha of 0.7385, indicating adequate internal consistency. While TS20 shows the lowest item-test correlation (0.6101), all items contribute meaningfully to the overall scale, highlighting the uncertainty and rapid changes in technology that can affect employees.

### **Overall Technostress Scale**

- **Overall Cronbach's Alpha:** 0.7986
- The comprehensive analysis of the Technostress Instrument yields an overall Cronbach's alpha of 0.7986, affirming the scale's reliability in measuring the multidimensional construct of technostress. Each subscale contributes significantly to the overall construct, with the Techno-Complexity subscale exhibiting the highest reliability scores.

### **4.6.2 Reliability of the Independent Work Performance Scale**

The IWP scale comprises three distinct sub-constructs: TP, CP, and CWB. This analysis evaluates the internal consistency of each subscale, as indicated by Cronbach's alpha, and summarises the overall reliability of the IWP scale.

#### **Task Performance (TP) Scale**

- Cronbach's Alpha: 0.6571
- The TP subscale shows a moderate level of internal consistency, with an alpha of 0.6571. The item-test correlations reveal that TP4 (0.6948) has the highest correlation, suggesting it is particularly effective in capturing task performance. However, the overall alpha score indicates that the subscale could benefit from item refinement, as TP3 (0.5594) demonstrates a lower correlation, indicating it may not align as closely with the overall construct.

#### **Contextual Performance (CP) Scale**

- Cronbach's Alpha: 0.7605

- The CP subscale exhibits a good level of reliability, with an alpha of 0.7605. The item-test correlations indicate that CP3 (0.7084) is a strong contributor to this construct. Conversely, CP8 shows the lowest correlation (0.4410), suggesting potential for improvement or reconsideration in its alignment with the overall subscale. Despite this, the remaining items contribute positively, and the subscale effectively captures contextual performance behaviours.

### **Counterproductive Work Behaviour (CWB) Scale**

- Cronbach's alpha: 0.8173
- The CWB subscale demonstrates excellent internal consistency, with an alpha of 0.8173. Two items (CWB3 = 0.8146 and CWB5 = 0.7414) contributed towards the strong item-test correlations of the subscale. Furthermore, all the items within the subscale showed strong item-test correlations. This high level of reliability indicates that the CWB scale is effective in measuring negative behaviours that detract from workplace performance.

### **Overall Independent Work Performance Scale**

- Overall Cronbach's Alpha: 0.7605
- The overall reliability of the IWP scale is good, reflected in an alpha of 0.7605. This indicates that the scale is generally reliable in measuring IWP across its various dimensions.

#### **4.6.3 Reliability of the Technology Self-Efficacy Scale**

The following section presents the reliability statistics of the technology self-efficacy (TSE) instrument. The TSE scale comprises six items that assess individuals' perceived competence in using technology to support teaching and learning. The reliability analysis of the TSE instrument was conducted through the use of Cronbach's alpha through item-test correlations.

#### **Reliability Statistics**

- Overall Cronbach's Alpha: 0.8069

- The overall reliability of the TSE scale is strong, with a Cronbach's alpha of 0.8069. This indicates that the scale is highly consistent in measuring TSE among respondents. **Table 4.20** presents the summary reliability scores of the TSE scale.

**Table 4.20: Reliability analysis of the TSE Scale**

| Item | Item-Test Correlation | Item-Rest Correlation | Alpha if Item Deleted |
|------|-----------------------|-----------------------|-----------------------|
| TSE1 | 0.6482                | 0.4970                | 0.7913                |
| TSE2 | 0.6609                | 0.4946                | 0.7925                |
| TSE3 | 0.7249                | 0.5884                | 0.7720                |
| TSE4 | 0.7516                | 0.6178                | 0.7648                |
| TSE5 | 0.7557                | 0.6093                | 0.7666                |
| TSE6 | 0.7355                | 0.5868                | 0.7719                |

#### 4.6.4 Reliability of the Proactive Personality Scale

The Proactive Personality (PP) scale consists of 17 items that assess an individual's tendency to take initiative and effect change in their environment. Below are the analysis results to evaluate the scale's internal consistency using Cronbach's alpha and item-test correlations. **Table 4.21** presents the summary reliability scores of the PP scale.

##### Reliability Statistics

- Overall Cronbach's Alpha: 0.9062
- The overall reliability of the PP scale is exceptionally high, indicating strong internal consistency among the items.

**Table 4.21: Reliability Analysis of the Proactive Personality Scale**

| Item  | Item-Test Correlation | Item-Rest Correlation | Alpha if Item Deleted |
|-------|-----------------------|-----------------------|-----------------------|
| PPS1  | 0.5409                | 0.4966                | 0.9036                |
| PPS2  | 0.5833                | 0.5312                | 0.9023                |
| PPS3  | 0.2490                | 0.1532                | 0.9141                |
| PPS4  | 0.6456                | 0.5921                | 0.9004                |
| PPS5  | 0.6251                | 0.5725                | 0.9010                |
| PPS6  | 0.6395                | 0.5897                | 0.9007                |
| PPS7  | 0.6517                | 0.5820                | 0.9008                |
| PPS8  | 0.7213                | 0.6711                | 0.8977                |
| PPS9  | 0.7011                | 0.6481                | 0.8985                |
| PPS10 | 0.6460                | 0.5694                | 0.9016                |
| PPS11 | 0.7320                | 0.6824                | 0.8973                |
| PPS12 | 0.7646                | 0.7261                | 0.8966                |

|              |        |        |        |
|--------------|--------|--------|--------|
| <b>PPS13</b> | 0.6330 | 0.5442 | 0.9038 |
| <b>PPS14</b> | 0.7113 | 0.6544 | 0.8981 |
| <b>PPS15</b> | 0.7444 | 0.7000 | 0.8970 |
| <b>PPS16</b> | 0.6752 | 0.6227 | 0.8994 |
| <b>PPS17</b> | 0.6433 | 0.5970 | 0.9007 |

**Item PPS1:**

- Item-test correlation of 0.5409 indicates a moderate contribution to the scale.
- Removing this item would slightly increase the overall alpha to 0.9036.

**Item PPS2:**

- This item shows a correlation of 0.5833, suggesting that it fairly aligns with the overall scale.
- Its removal would increase alpha to 0.9023, indicating it is a moderately important item.

**Item PPS3:**

- This reverse-coded item has a low item-test correlation (0.2490) and its removal would increase the overall alpha to 0.9141.
- This suggests it may not align well with the construct being measured.

**Item PPS4:**

- With a correlation of 0.6456, this item makes a positive contribution to the scale.
- Removing it would slightly lower the alpha to 0.9004, indicating its relevance.

**Item PPS5:**

- This item exhibits a strong correlation (0.6251) and makes a significant contribution, with an alpha of 0.9010 if removed.

**Items PPS6 to PPS17:**

- All other items show significant positive correlations (ranging from 0.5409 to 0.7646), and their removal results in very slight decreases in alpha, confirming their relevance.

## 4.7 FACTOR ANALYSIS

Factor analysis was conducted to analyse the relationships between technostress, IWP, TSE and proactive personality. According to Shrestha (2021), factor analysis is helpful in analysing relationships among observed variables to discover latent constructs that are not readily apparent. Moreover, the use of factor analysis is especially beneficial in complex social science studies, such as technostress studies, wherein multiple variables and dimensions are connected.

In this study, conducting factor analysis is essential for several reasons:

- It aids in validating the instrument utilised in the research, ensuring that the items accurately reflect the theoretical constructs they aim to measure.
- By grouping related items together, factor analysis can confirm whether the factors of technostress, such as overload, complexity, insecurity, and uncertainty, are distinct yet interrelated components of a broader phenomenon.

The Bartlett test of sphericity and the Kaiser-Meyer-Olkin (KMO) are two statistical techniques that are significant in assessing the appropriateness of factor analysis. The Bartlett test of sphericity is used to evaluate if the correlation matrix is significantly different from an identity matrix, which would indicate that the variables are not interrelated. The Bartlett test of significance (i.e.  $p < 0.05$ ) suggests that there are correlations among the variables, confirming that factor analysis can be conducted. The KMO, on the other hand, measures sampling adequacy by calculating the proportion of variance among the variables that might be common variance. A KMO value close to 1 indicates that factor analysis is appropriate, while values below 0.5 suggest that the data may not be suitable for such analysis.

Moreover, conducting factor analysis reduces dimensionality, allowing researchers to summarise information without losing significant data variability. This simplification enhances the interpretability of results and facilitates the development of a coherent framework to assess the influence of technostress on individual work performance.

#### **4.7.1 KMO for Sampling adequacy for the Technostress scale**

This section presents the KMO values and Bartlett test of sphericity of the instruments adopted in this study to determine factorability.

##### **1. Techno-overload (TS1 - TS6):**

- The techno-overload sub-scale yielded a KMO value of 0.607 indicating a moderate level of sampling adequacy, suggesting that the data are suitable for factor analysis.
- The Bartlett's Test yielded a significant chi-square value (221.035,  $p < 0.001$ ) demonstrating a significant correlation among the variables, justifying the use of factor analysis for this sub-scale.

##### **2. Techno-complexity (TS10 - TS14):**

- The techno-complexity sub-scale had a KMO value of 0.779. This suggests a good level of sampling adequacy, reinforcing the appropriateness of the data for factor analysis.
- With regards to the Bartlett's Test, the results yielded a high chi-square value (340.045,  $p < 0.001$ ) confirming that the variables are interrelated, indicating the presence of a latent factor underlying this set of items.

##### **3. Techno-Insecurity (TS15 - TS19):**

- KMO: 0.846, indicating a very good level of sampling adequacy, and suggests that the items are well correlated and suitable for factor analysis.
- Bartlett's Test: The chi-square value (464.406,  $p < 0.001$ ) further supports the notion that these variables are interrelated.

##### **4. Techno-Uncertainty (TS20 - TS23):**

- KMO: 0.676 suggests a moderate to good level of sampling adequacy.
- Bartlett's Test: A significant chi-square value (313.958,  $p < 0.001$ ) indicates that the variables in this scale also exhibit significant intercorrelations.

The results from the factor analysis suggest that the technostress scale effectively captures distinct dimensions of technostress that individuals face in a higher educational institution. Each Technostress sub-scale (i.e. Techno-overload, Techno-complexity, Techno-insecurity, and Techno-uncertainty) exhibits strong inter-item correlations, supporting their conceptual validity.

- **Techno-overload** reflects how technology may compel individuals to work faster, manage increased workloads, and alter their work habits, potentially leading to stress and burnout.
- **Techno-complexity** indicates challenges in understanding and using new technologies, highlighting a need for better training and support systems to mitigate feelings of inadequacy and frustration.
- **Techno-insecurity** reveals a pervasive concern over job security in the face of evolving technology, emphasising the importance of creating an environment that encourages knowledge sharing and collaboration among colleagues.
- **Techno-uncertainty** addresses the continuous evolution of technology within organisations, suggesting that institutions must manage change effectively to reduce anxiety associated with constant upgrades and new developments.

#### 4.7.2 KMO Sampling Adequacy for IWP Scale

The factor analysis results for the TP, CP, and CWB sub-scales provide valuable insights into the measurement structure of these constructs in your study. Below is a summary analysis of each IWP sub-scale based on the findings (**Table 4.22**).

**Table 4.22: Factor analysis of the IWP scale**

| Factor                                    | KMO   | Determinant  | Chi-square | Degrees of Freedom | p-value | H <sub>0</sub> : Variables are Not Intercorrelated |
|-------------------------------------------|-------|--------------|------------|--------------------|---------|----------------------------------------------------|
| Task Performance (TP1 - TP5)              | 0.557 | 0.425        | 257.118    | 10                 | 0.000   | Reject                                             |
| Contextual Performance (CP1 - CP8)        | 0.738 | 0.152        | 564.022    | 28                 | 0.000   | Reject                                             |
| Collaborative Work Behavior (CWB1 - CWB5) | 0.730 | Not Provided | 597.126    | 10                 | 0.000   | Reject                                             |

As indicated in section 4.3, the IWP scales consisted of three sub-scales: TP, CP and CWB. Below is a detailed analysis of the findings for each sub-scale.

### 1. Task Performance Scale

- **KMO Value:** 0.557, indicating marginal sampling adequacy. This suggests that the variables may not be ideally suited for factor analysis but are still usable. Future research may benefit from refining the TP scale items to improve intercorrelation.
- **Bartlett's Test:** The chi-square value of 257.118 with a p-value of 0.000 confirms that the items are significantly correlated, allowing for the possibility of underlying factors.
- **Interpretation:** The TP items focus on how well respondents manage their workload and achieve results. Given the moderate KMO, there may be variability in responses that could affect the reliability of the factor structure. Ensuring clarity in how respondents understand each item could enhance the validity of this scale.

### 2. Contextual Performance Scale

- **KMO Value:** 0.738, indicating good sampling adequacy. This suggests that the variables are well-suited for factor analysis.
- **Bartlett's Test:** The chi-square value of 564.022 with a p-value of 0.000 supports the intercorrelation of items, indicating a robust underlying factor structure.
- **Interpretation:** The CP items assess the proactive and supportive behaviours of employees that go beyond basic job requirements. The high KMO suggests that respondents are likely to engage consistently in these behaviours, making the CP scale a reliable measure of contextual performance.

### 3. Counterproductive Work Behavior Scale

- **KMO Value:** Not provided, but the Bartlett test yields a chi-square value of 597.126 with a p-value of 0.000. This significant result indicates that the CWB items are interrelated.
- **Interpretation:** The CWB items reflect negative behaviours that hinder organisational effectiveness. While the KMO value is missing, the significant Bartlett test suggests that these items also exhibit meaningful correlations.

Enhancing the clarity of the CWB items could further strengthen their measurement reliability.

In the context of this study, the factor analysis results highlight the meticulous nature of work-stress-related behaviours among academic staff. While the CP scale shows strong reliability and interrelation among its items, the TP scale requires careful consideration due to its marginal KMO value. Furthermore, the CWB scale also demonstrates significant interrelations; however, further evaluation of its measurement properties would yield numerous benefits.

#### 4.7.3 Factor Analysis of the Technology Self-Efficacy Scale

The factor analysis results for the Technology Self-Efficacy (TSE) scale provide significant insights into its measurement structure and effectiveness in assessing respondents' perceived capabilities in using technology for educational purposes.

**Table 4.23** presents the summary factor analysis findings of the TSE scale.

**Table 4.23: Factor analysis of the TSE scale**

| Measure                                  | Value   | Interpretation                                                                      |
|------------------------------------------|---------|-------------------------------------------------------------------------------------|
| <b>Kaiser-Meyer-Olkin (KMO) Measure</b>  | 0.715   | Good sampling adequacy, indicating suitability for factor analysis.                 |
| <b>Bartlett's Test of Sphericity</b>     |         |                                                                                     |
| - Chi-square                             | 612.234 | A highly significant result ( $p = 0.000$ ) indicates intercorrelation among items. |
| - Degrees of Freedom                     | 15      |                                                                                     |
| <b>Determinant of Correlation Matrix</b> | 0.130   | Indicates some multicollinearity but is acceptable for analysis.                    |

##### 1. KMO Measure of Sampling Adequacy

- **KMO Value:** 0.715 indicates good sampling adequacy. This suggests that the variables are sufficiently correlated to justify the application of factor analysis. A KMO value above 0.7 is generally considered acceptable, indicating that the items can effectively measure a common underlying construct.

##### 2. Bartlett's Test of Sphericity

- **Chi-square Value:** 612.234 with 15 degrees of freedom and a p-value of 0.000. This result is highly significant, indicating that the null hypothesis (that the

variables are not intercorrelated) can be rejected. The significant chi-square value suggests that the items of the TSE scale are correlated and that it is appropriate to proceed with factor analysis.

### 3. Determinant of the Correlation Matrix

- **Determinant Value:** 0.130. Although the determinant value is not exceedingly low, indicating potential multicollinearity, the overall findings from the KMO and Bartlett tests suggest that the scale is still suitable for factor analysis. It's essential to monitor the correlations among items to ensure no excessive redundancy exists.

### Interpretation of the Technology Self-Efficacy Scale

The TSE scale comprises six items that assess various aspects of respondents' self-perceived competence in using technology in educational settings. The scale employs a 6-point Likert response format, ranging from 1 (Not at All) to 6 (A Great Deal), which provides a refined view of respondents' self-efficacy.

### Scale Items Analysis

1. **Preparation to Evaluate Software:** This item assesses the readiness of respondents to evaluate technological tools critically. A high rating would imply a strong belief in their evaluative skills, which are essential for effective teaching.
2. **Integration Across the Curriculum:** This item looks at respondents' perceived ability to integrate technology into various subjects. High scores indicate confidence in a holistic approach to technology use in education.
3. **Competence in Selecting and Using Media:** This item gauges respondents' confidence in their ability to choose appropriate media for teaching. A high self-efficacy rating here would suggest that respondents feel well-equipped to enhance learning through technology.
4. **Determining Usage of Technology:** Respondents rate their capability in knowing when and how to use technology. A strong self-efficacy belief in this area is crucial for making informed pedagogical decisions.

5. **Incorporating Technology in Field Experience:** This practical application item evaluates how effectively respondents implemented technology during their teaching practice. High self-ratings here would demonstrate a direct application of their perceived skills.
6. **Preparedness for Assistive Technologies:** This item focuses on the confidence to select and use technologies that support diverse learners. High scores suggest an awareness of and readiness to accommodate varying student needs.

#### 4.7.4 Factor Analysis of the Proactive Personality Scale

The Proactive Personality Scale (PPS) factor analysis results provide valuable insights into the measurement structure of proactive traits among respondents. **Table 4.24** below presents a detailed analysis of the findings for the PPS scale.

**Table 4.24: Summary Table of Findings of Proactive Personality Scale**

| Measure                                 | Value    | Interpretation                                                                      |
|-----------------------------------------|----------|-------------------------------------------------------------------------------------|
| <b>Kaiser-Meyer-Olkin (KMO) Measure</b> | 0.894    | Excellent sampling adequacy, indicating suitability for factor analysis.            |
| <b>Bartlett's Test of Sphericity</b>    |          |                                                                                     |
| - Chi-square                            | 2422.093 | Highly significant result ( $p = 0.000$ ), indicating intercorrelation among items. |
| - Degrees of Freedom                    | 136      |                                                                                     |

The findings from the KMO measure of sampling adequacy indicated a KMO Value of 0.894, which means excellent sampling adequacy. A KMO value above 0.8 is considered very good, suggesting that the variables are highly correlated and suitable for factor analysis. Furthermore, Bartlett's Test of Sphericity yielded a Chi-square Value of 2422.093 with 136 degrees of freedom and a p-value of 0.000. This highly significant result indicates that the null hypothesis (the variables are not intercorrelated) can be rejected. The significant chi-square value suggests that the items of the PPS Scale are correlated and that factor analysis is appropriate.

#### 4.8 CONFIRMATORY FACTOR ANALYSIS

This section describes the factor analysis used to condense the large set of items in this study down to a more manageable number of factors. Two approaches to factor

analysis can be considered: Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA). Confirmatory Factor Analysis (CFA) is a specialised statistical technique used to test whether a set of observed variables represents the number of factors and the relationships between them, as hypothesised. A CFA tests how well a measurement theory fits reality “as captured by data”. At the same time, an EFA explores the data structure to determine which and how many dimensions are needed to represent the data (Pallant, 2011:181). According to Hair *et al.* (2018), an EFA is conducted when the researcher does not know how many variables exist and to which dimensions they are assigned. On the other hand, CFA plays a crucial role in validating the constructs and measurement models within a study, ensuring that the observed data accurately represent the theoretical constructs of interest.

In the context of South African educational research, particularly in HEIs, where socio-economic diversity and complex interrelationships between variables are common, CFA becomes vital in establishing the reliability and validity of constructs. The rigorous application of CFA and EFA enhances the credibility of research findings and informs policy-making and intervention strategies based on sound empirical evidence. The CFA conducted in this study involved a Structural Equation Modeling (SEM) approach to analyse relationships among latent variables. The model specified five latent variables (TS1 to TS5, representing various constructs related to the study) alongside endogenous and exogenous observed variables.

#### 4.8.1 Model Fitting Results

The iteration process for determine model fit revealed the following log-likelihood values across iterations. **Table 4.25** presents the model log-likelihood results:

**Table 4.25: Model log-likelihood results**

| Iteration | Log Likelihood |
|-----------|----------------|
| 0         | -25447.594     |
| 1         | -24927.253     |
| 2         | -24767.331     |
| 3         | -24724.675     |
| 4         | -24653.334     |
| 5         | -24647.270     |
| 6         | -24646.988     |

|   |            |
|---|------------|
| 7 | -24646.987 |
|---|------------|

The final log-likelihood of -24646.987 indicates the model's fit to the observed data, with lower log-likelihood values suggesting a better model fit.

The results from the CFA provide several important insights:

1. **Model Fit:** The convergence of log-likelihood values across iterations suggests that the specified model is appropriate for the observed data. This indicates successfully identifying the relationships between the latent constructs and their respective observed variables.
2. **Construct Validation:** By fixing the first observed variable of each latent construct to 1, the model effectively standardises the measurement scales for each factor, allowing for direct interpretation of relationships among constructs. This is essential in ensuring that each latent variable is validly and reliably measured.
3. **Endogenous and Exogenous Variables:** The distinction between endogenous (dependent) and exogenous (independent) variables in the analysis clarifies the causal pathways and the interdependencies among constructs. The presence of 304 observations strengthens the robustness of the findings, enhancing the generalisability of the model to the broader South African context.
4. **Theoretical Implications:** The successful specification of the model supports the theoretical framework underpinning this research. It affirms that the latent constructs represented by TS1 to TS5, TP, CP, CWB, SE, and PPS are relevant and can be used to understand the complex interrelationships among variables in this context.

#### 4.8.2 Recommended fit indices

Table 4.26 summarises the fit indices assessment performed in the model of this study.

**Table 4.26: Goodness of fit measures applied to this study**

| Goodness of Fit Measure | Model Fit | Threshold     |
|-------------------------|-----------|---------------|
| Absolute Fit Indices    |           |               |
| Chi-square              | 4.334     | >5 = Terrible |

|                                                 |       |                                                                 |
|-------------------------------------------------|-------|-----------------------------------------------------------------|
|                                                 |       | 3-5 = Acceptable<br><3 = Excellent                              |
| Goodness-of-fit Index (GFI)                     | 0.79  | <0.90 = Terrible<br>>0.90 = Acceptable<br>>0.95 = Excellent     |
| Root Mean Square Error of Approximation (RMSEA) | 0.069 | >0.08 = Terrible<br>0.06-0.08 = Acceptable<br><0.06 = Excellent |
| <b>Relative Indices</b>                         |       |                                                                 |
| Comparative Fit Index (CFI)                     | 0.691 | <0.90 = Terrible<br>0.90-0.95 = Acceptable<br>>0.95 = Excellent |
| Tucker–Lewis index (TLI)                        | 0.673 | <0.90 = Terrible<br>0.90-0.95 = Acceptable<br>>0.95 = Excellent |

The goodness-of-fit indices were applied in this study to assess how well the model fits the observed data. The Chi-square statistic yielded a value of 4.335, indicating an acceptable fit as it falls within the 3–5 range. However, the Goodness-of-Fit Index (GFI) at 0.79 suggests a suboptimal fit, as it is below the acceptable threshold of 0.90. The Root Mean Square Error of Approximation (RMSEA) was 0.091, slightly above the acceptable range (0.06–0.08), indicating potential room for model improvement.

Relative fit indices, including the Comparative Fit Index (CFI) and Tucker–Lewis Index (TLI), also pointed to areas where the model could be refined. The CFI value of 0.76 and the TLI value of 0.673 fell below the acceptable range of 0.90, reflecting a less-than-ideal comparative fit. These fit indices reveal that while certain model aspects meet minimum fit criteria, further model adjustments may enhance overall fit, particularly regarding the relative index.

#### 4.8.3 Fit indices threshold applied in this study

**Table 4.27** summarises the findings of the fit statistics for the model proposed for this study.

**Table 4.27: Model fit statistics**

| Fit Statistic                     | Value     | Description                |
|-----------------------------------|-----------|----------------------------|
| <b>Likelihood Ratio</b>           |           |                            |
| $\chi^2$ (model vs. saturated)    | 4333.852  | Model vs. saturated fit    |
| $p > \chi^2$                      | 0.000     |                            |
| $\chi^2$ (baseline vs. saturated) | 10156.317 | Baseline vs. saturated fit |
| $p > \chi^2$                      | 0.000     |                            |
| <b>Population Error</b>           |           |                            |

|                             |           |                                            |
|-----------------------------|-----------|--------------------------------------------|
| RMSEA                       | 0.069     | Root Mean Squared Error of Approximation   |
| 90% CI (lower bound)        | 0.066     | Lower bound of the 90% confidence interval |
| 90% CI (upper bound)        | 0.071     | Upper bound of the 90% confidence interval |
| Pclose                      | 0.000     | Probability RMSEA $\leq$ 0.05              |
| <b>Information Criteria</b> |           |                                            |
| AIC                         | 48154.361 | Akaike's Information Criterion             |
| BIC                         | 49012.994 | Bayesian Information Criterion             |
| <b>Baseline Comparison</b>  |           |                                            |
| CFI                         | 0.691     | Comparative Fit Index                      |
| TLI                         | 0.673     | Tucker-Lewis Index                         |
| Size of Residuals           |           |                                            |
| SRMR                        | 0.078     | Standardised Root Mean Squared Residual    |
| CD                          | 1.000     | Coefficient of Determination               |

#### 4.8.4 Likelihood Ratio Tests

The Likelihood Ratio Test (LRT) is a statistical method for comparing the goodness of fit between two competing models, typically a null model (constrained) and an alternative model (unconstrained).

- Chi-squared (Model vs. Saturated): The value of 4658.314 with a p-value of 0.000 indicates that the model significantly differs from the saturated model, which fits the data perfectly. This suggests that the model does not perfectly capture the data structure, which is expected in practical applications.
- Chi-squared (Baseline vs. Saturated): The baseline chi-squared of 10518.798 ( $p = 0.000$ ) indicates that the baseline model (a simple model with no parameters) also significantly differs from the saturated model. This suggests that the proposed model offers a better fit than a simplistic one.

#### Population Error

- RMSEA (Root Mean Squared Error of Approximation): An RMSEA value of 0.069 suggests a reasonable fit. Generally, RMSEA values less than 0.08 are considered acceptable, and values below 0.05 indicate a good fit. The 90% confidence interval (0.066 to 0.072) further supports that the model fit is within an acceptable range. The p-value of 0.000 indicates that the probability of RMSEA being less than or equal to 0.05 is very low, suggesting that the model may not be a perfect fit.

### Information Criteria

- AIC (Akaike's Information Criterion): The AIC value of 49767.975 is used for model comparison; lower values indicate better fit when comparing multiple models.
- BIC (Bayesian Information Criterion): The BIC value of 50648.910 also serves a similar purpose as AIC but penalises complexity more heavily. Again, lower values are preferable.

### Baseline Comparison

- CFI (Comparative Fit Index): A CFI value of 0.676 indicates a moderate fit, as values closer to 1 indicate a better fit. A CFI of 0.90 or above is typically desired.
- TLI (Tucker–Lewis Index): The TLI value of 0.658 also suggests a moderate fit, similar to the CFI.

### Size of Residuals

- SRMR (Standardised Root Mean Squared Residual): An SRMR value of 0.080 is considered acceptable but indicates some areas of potential misfit. Values less than 0.08 are generally seen as indicative of a good fit.
- Coefficient of Determination (CD): A CD value of 1.000 suggests that the model explains all the variance in the dependent variable, which may imply an overfitting scenario or a perfect fit in this context.

Overall, while the model demonstrates some aspects of a reasonable fit (especially the RMSEA), the CFI and TLI fit indices indicate that there is room for model improvement.

#### 4.8.5 Convergent and Discriminant Validity Assessment

Convergent validity refers to the degree to which two measures that are supposed to be related correlate. This assesses whether indicators of a particular construct are strongly correlated. Discriminant validity, also known as divergent validity, assesses whether concepts or measurements that are not supposed to be related are unrelated.

**Table 4.28** summarises the squared correlations among latent variables, which is essential for determining convergent and discriminant validity.

**Table 4.28: Squared correlations of latent variables**

|     | TS1   | TS2   | TS3   | TS4   | TS5   | TP    | CP    | CWB   | SE    | PPS   |
|-----|-------|-------|-------|-------|-------|-------|-------|-------|-------|-------|
| TS1 | 1.000 |       |       |       |       |       |       |       |       |       |
| TS2 | 0.250 | 1.000 |       |       |       |       |       |       |       |       |
| TS3 | 0.318 | 0.180 | 1.000 |       |       |       |       |       |       |       |
| TS4 | 0.162 | 0.063 | 0.538 | 1.000 |       |       |       |       |       |       |
| TS5 | 0.095 | 0.035 | 0.029 | 0.016 | 1.000 |       |       |       |       |       |
| TP  | 0.008 | 0.000 | 0.013 | 0.008 | 0.036 | 1.000 |       |       |       |       |
| CP  | 0.009 | 0.008 | 0.024 | 0.001 | 0.010 | 0.062 | 1.000 |       |       |       |
| CWB | 0.089 | 0.016 | 0.284 | 0.266 | 0.007 | 0.028 | 0.006 | 1.000 |       |       |
| SE  | 0.008 | 0.014 | 0.060 | 0.011 | 0.013 | 0.151 | 0.033 | 0.001 | 1.000 |       |
| PPS | 0.014 | 0.000 | 0.006 | 0.000 | 0.032 | 0.072 | 0.096 | 0.000 | 0.111 | 1.000 |

#### **For Convergent Validity:**

TS1, TS2, TS3, TS4: These variables show moderate correlations among themselves (e.g., TS1 and TS3 = 0.318), indicating that they are likely measuring related constructs. However, correlations between some pairs (like TS1 and TS2 at 0.250) suggest a need for further analysis.

#### **Discriminant Validity**

As stated above, discriminant validity ensures that constructs that should not be related are indeed distinct. In the context of this study, variables such as TP and TS1 show a very low correlation of 0.008, indicating that these constructs are distinct from one another. Similarly, CP and others have low correlations with TS variables, suggesting that they measure different aspects.

#### **Inter-Variable Relationships:**

Some variables (for example, CWB, have moderate correlations with others (e.g., TS3 = 0.284), suggesting they may share some common underlying factors. Conversely, many TS variables have low correlations with TP, CP, and PPS (Positive Psychological States), suggesting they do not overlap significantly with these constructs.

#### 4.8.6 Interpretation of AVE results

Regarding convergent validity, only AVE\_TS2 and AVE\_TS3 meet the acceptable threshold of 0.5, indicating that these constructs are measuring their intended variables adequately (see **Table 4.29**). The remaining variables fall short, suggesting that the items used may not effectively capture the constructs. As for discriminant validity, all constructs, except AVE\_TS2 and AVE\_TS3, show problematic discriminant validity, indicating significant overlap with other constructs. This suggests that the distinctions between these latent variables may not be clearly defined. As such, the results indicate a need to revise the measurement items and perhaps the constructs to improve convergent and discriminant validity. Addressing these issues will help ensure the constructs are distinct and accurately measured in this study.

**Table 4.29: AVE results summary table**

| Latent Variable | AVE   | Convergent Validity       | Discriminant Validity |
|-----------------|-------|---------------------------|-----------------------|
| AVE_TS1         | 0.413 | Problematic (below 0.5)   | Problematic           |
| AVE_TS2         | 0.508 | Acceptable ( $\geq 0.5$ ) | Problematic           |
| AVE_TS3         | 0.500 | Acceptable                | Problematic           |
| AVE_TS4         | 0.434 | Problematic               | Problematic           |
| AVE_TS5         | 0.432 | Problematic               | Problematic           |
| AVE_TP          | 0.282 | Problematic               | Problematic           |
| AVE_CP          | 0.292 | Problematic               | Problematic           |
| AVE_CWB         | 0.478 | Problematic               | Problematic           |
| AVE_SE          | 0.416 | Problematic               | Problematic           |
| AVE_PPS         | 0.394 | Problematic               | Problematic           |

#### 4.8.7 Revision of Dimensions

As presented above, the original model showed a poor fit. The researcher proceeded to make the following adjustments to improve its fit. This was done by deleting problematic items with offending factor loadings ( $<0.50$ ). **Table 4.30** depicts the CFA results of the revised model.

**Table 4.30: Summary Table of Confirmatory Factor Analysis Results**

| Component            | Details                                                                                                                               |
|----------------------|---------------------------------------------------------------------------------------------------------------------------------------|
| Model Fit            | Log Likelihood: -23846.18                                                                                                             |
| Endogenous Variables | Measurement: ts1-ts6, ts7-ts9, ts10-ts14, ts15-ts19, ts20-ts23, tp1-tp5, cp1-cp3, cp4-cp7, cwb1-cwb5, se1-se6, pps1, pps2, pps4-pps17 |
| Exogenous Variables  | Latent: TS1, TS2, TS3, TS4, TS5, TP, CP, CWB, SE, PPS                                                                                 |
| Iterations           | 10 iterations were conducted to reach the log-likelihood                                                                              |

- **Model Fit:** The final log-likelihood of -23846.18 suggests that the model has undergone multiple iterations to achieve convergence. While a single log-likelihood value does not indicate fit quality alone, a consistent improvement across iterations implies that the model is refining towards an optimal solution.
- **Endogenous and Exogenous Variables:** The table lists the endogenous (measured) and exogenous (latent) variables. Removing items with factor loadings below 0.50 indicates a focus on retaining only the strongest indicators for each latent variable, enhancing the model's overall validity.
- **Iteration Process:** The iteration details show that the model required 10 iterations to stabilise. The variations in log-likelihood across iterations indicate the model was adjusted to improve fit. However, some iterations reported "not concave," which could suggest areas where the model could still be optimised.

The refined analysis suggests that the confirmatory factor model has been refined by eliminating weaker variables, likely resulting in a more robust representation of the latent constructs. Additionally, a continued assessment of fit indices such as RMSEA and CFI would provide further insights into the model's overall adequacy.

The results from the CFA provide significant insights into the measurement model, following the removal of variables with factor loadings below 0.5 (see **Table 4.31**). The CFA model was specified with latent constructs representing key factors in the study framework, including Technostress (TS1–TS5), TP, CP, CWB, TSE, and PP. Several observed indicators measured each latent construct. For instance, the latent variable TS1 was represented by six indicators (TS1–TS6), while TP was measured through five indicators (TP1–TP5). This structural alignment of constructs and indicators reflects the hypothesised relationships within the model, with each latent construct capturing variance in its associated indicators as per theoretical expectations.

**Table 4.31: Structural Equation Model Summary**

| Aspect            | Details                 |
|-------------------|-------------------------|
| Sample Size       | 304                     |
| Estimation Method | Maximum Likelihood (ml) |
| Log Likelihood    | -23846.18               |
| Fixed Parameters  |                         |

|  |                |
|--|----------------|
|  | [ts1] TS1 = 1  |
|  | [ts7] TS2 = 1  |
|  | [ts10] TS3 = 1 |
|  | [ts15] TS4 = 1 |
|  | [ts20] TS5 = 1 |
|  | [tp1] TP = 1   |
|  | [cp1] CP = 1   |
|  | [cwb1] CWB = 1 |
|  | [se1] SE = 1   |
|  | [pps1] PPS = 1 |

The model estimation involved multiple iterations, converging at a log-likelihood value of -23846.18 after ten rounds. The iterative process and steady improvement in log-likelihood values signify a reliable model. Achieving convergence indicates that the model's parameters, such as factor loadings and latent variable relationships, were successfully estimated, providing a robust measurement foundation.

To maintain the model's identification, each factor included a reference indicator set to 1 (e.g., [ts1] TS1 = 1 for the Technostress construct TS1). This practice helped define the scale for each latent variable and ensured that all latent constructs were identifiable within the model. After standardisation, the factor loadings and relationships are easier to interpret, allowing a deeper understanding of how well each observed variable represents its respective latent construct. Removing indicators with low factor loadings ( $< 0.5$ ) also improved the model's fit, suggesting that the retained indicators accurately reflect the latent variables in question. The CFA results indicate a satisfactory measurement model with stable, interpretable factor loadings and construct relationships. The observed convergence and model fit contribute to the reliability of the hypothesised constructs and support the theoretical framework of this study.

#### **4.9 CONFIRMATORY FACTOR ANALYSIS (WITH FURTHER ADJUSTMENT)**

As presented above, the revised model showed a poor fit after the initial revision. The researcher proceeded to make the following further adjustments to improve the fit. Some items showed factor loadings of  $< 0.50$  and were deleted to reduce model redundancy. Item wording was checked to see if respondents could perceive them as too similar. The items with the lowest factor loadings were removed one after the other.

### Model Specification:

Each latent variable is measured using multiple observed (indicator) variables, as indicated by the arrows (See Figure 4.6). For example, TS1 is measured by TS1 to TS6, and TS2 is measured by ts7 to TS9.

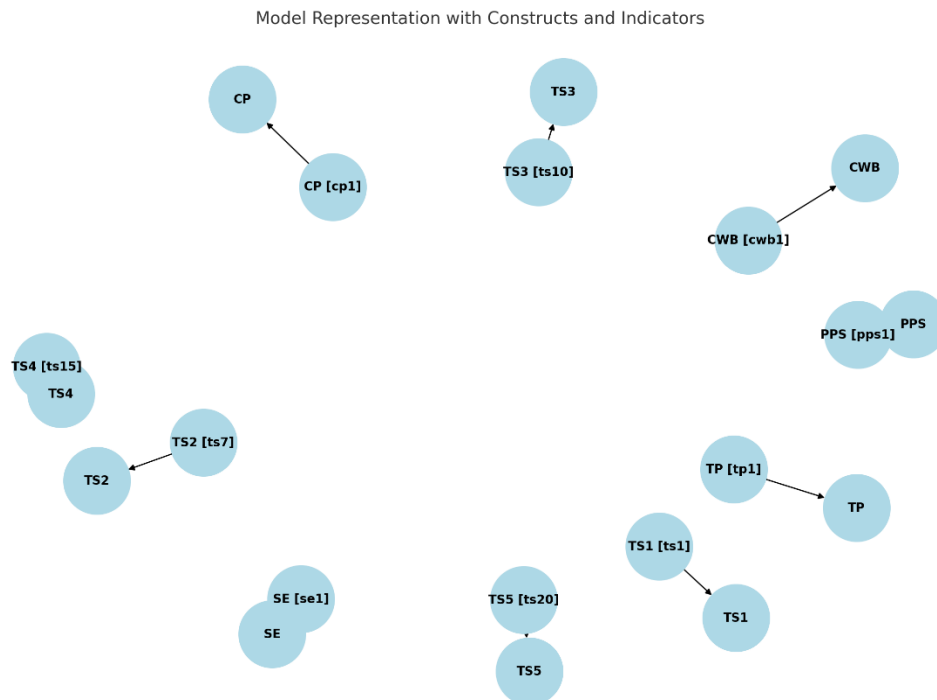


**Figure 4.6: Model representation with constructs and indicators**

The model converged after seven iterations, with the log-likelihood stabilising at -22481.459. The iterations show improvement in the model fit as the log-likelihood values decrease and stabilise. The model used the maximum likelihood (ML) estimation method, which assumes multivariate normality and maximises the probability of the data fitting the specified model.

The results are standardised, meaning the coefficients (loadings and paths) are scaled to allow comparison across indicators. This simplifies interpretation by rescaling variables with a mean of 0 and a standard deviation of 1. For each latent variable, indicators (e.g., ts1, ts7, tp1, etc.) have been set to 1. Scaling latent variables and making them identifiable is a common practice in SEM.

#### 4.9.1 Fit indices assessment of the revised

##### *Model Fit Evaluation (Likelihood Ratio Test)*

To evaluate the fitness of the revised model, the researcher used the likelihood ratio test to assess the difference between the hypothesised model and the saturated model, representing the best possible fit to the data. In this study, the likelihood ratio for the model versus the saturated model is  $X^2_{ms}(1550) = 3675.882$ ,  $p < 0.001$ . This significant result suggests that the hypothesised model does not fit the data, and the saturated model does not fit the data either. However, the  $X^2$  test is sensitive to large sample sizes (for example,  $n=304$ , as in this study) and complex models, often leading to rejecting the null hypothesis even if the model exhibits a reasonable fit.

The comparison between the baseline and saturated models also shows a significant result. This is expected, as the baseline model is highly restrictive and assumes no relationships among variables, which is an unrealistic scenario. The results from the CFA (after further adjustment) provide significant insights into the measurement model, following the removal of variables with factor loadings below 0.5 (see **Table 4.32**).

**Table 4.32: Structural Equation Model Summary**

| Aspect            | Details                 |
|-------------------|-------------------------|
| Sample Size       | 304                     |
| Estimation method | Maximum likelihood (ml) |
| Log-likelihood    | -22481.459              |
| [ts1]TS1          | = 1                     |
| [ts7]TS2          | = 1                     |
| [ts10]TS3         | = 1                     |
| [ts15]TS4         | = 1                     |
| [ts20]TS5         | = 1                     |
| [tp1]TP           | = 1                     |
| [cp1]CP           | = 1                     |
| [cwb1]CWB         | = 1                     |
| [se1]SE           | = 1                     |
| [pps1]PPS         | = 1                     |

##### *Population Error*

The Root Mean Squared Error of Approximation (RMSEA) was used to evaluate the error of approximation in the population. An RMSEA value of 0.067 indicates an acceptable fit, falling within the range of 0.05 to 0.08. Additionally, the 90% confidence

interval for RMSEA (0.064–0.070) supports the interpretation that the model's approximation error is within an acceptable range. However, the probability that RMSEA is less than or equal to 0.05 ( $p_{close} = 0.000$ ) tests whether the model fits the data closely. The significant result ( $p_{close} = 0.000$ ) indicates that the null hypothesis ( $RMSEA \leq 0.05$ ) is rejected, suggesting that the model does not exhibit a close fit.

### *Information Criteria*

The Akaike Information Criterion ( $AIC = 45400.917$ ) and Bayesian Information Criterion ( $BIC = 46214.946$ ) are relative fit indices that compare competing models. Lower values indicate better fit, but these metrics are most informative when comparing multiple models. These values are reported for reference as no alternative models are presented here.

### *Baseline Comparison*

The Comparative Fit Index (CFI) and Tucker–Lewis Index (TLI) were used to compare the revised hypothesised model to the baseline model while accounting for model complexity.

- CFI = 0.723: The CFI compares the hypothesised model to the baseline model and adjusts for complexity. A value below 0.90 indicates a poor fit. In this case, a CFI of 0.723 suggests that the model does not adequately explain the observed data compared to the baseline model.
- TLI = 0.705: The TLI penalises model complexity more heavily than the CFI. Similarly, a value below 0.90 indicates a poor fit. The TLI of 0.705 confirms that the model's performance is sub-optimal.

### *Size of Residuals*

The Standardised Root Mean Squared Residual (SRMR) was used to evaluate the residuals or differences between the observed and predicted correlations. An SRMR

value of 0.075 falls below the threshold of 0.08, indicating a good fit. Furthermore, the Coefficient of Determination ( $CD = 1.000$ ) reflects the proportion of variance in the observed data explained by the model. A CD value of 1.000 indicates that the model accounts for all observed variance, representing an ideal outcome.

The results of the model fit evaluation highlight both strengths and weaknesses:

- Strengths:
  - RMSEA (0.067) and SRMR (0.075) indicate an acceptable to good fit.
  - The Coefficient of Determination ( $CD = 1.000$ ) demonstrates that the model explains the observed variance effectively.
- Weaknesses:
  - The likelihood ratio test  $X^2$  is significant, but this is expected due to the test's sensitivity to large sample sizes and complex models.
  - The CFI (0.723) and TLI (0.705) values suggest poor fit, indicating that the model structure may require refinement to improve fit.

After further adjustment, the CFA evaluation suggests that while certain model aspects demonstrate acceptable fit, other metrics highlight the need for potential adjustments to improve overall performance. Future efforts may focus on refining the model by addressing weak indicators, adding theoretically justified covariances, or simplifying the model structure to enhance fit indices like CFI and TLI.

#### **4.9.2 Justification for the Use of Multivariate Multiple Regression (MMR) Analysis**

During the analysis phase of this study, it was discovered that the model did not show a good fit to proceed with SEM analysis (as discussed above) in order to assess the moderating effects of TSE and PP. In response, the researcher consulted relevant literature and identified similar challenges in other studies. Furthermore, the services of a qualified Statistician were utilised for recommendations on the appropriate alternative method with regards to the development of a framework. After consulting the literature, scholars recommended using Multivariate Multiple Regression (MMR) as an alternative approach to analysing the relationships between multiple constructs of the independent variable and independent variables, mainly where moderators are

involved (Cheung *et al.*, 2021). Other scholars suggested modifying the SEM model by adding or removing paths based on theoretical justification and modification indices while cautioning against overfitting, which could compromise the model's validity.

MMR is a robust statistical method recommended for analysing relationships involving multiple dependent and independent variables, particularly when moderators are included (Mertler, Vannatta & LaVenia, 2021). In the context of this study, the researcher opted to utilise MMR to advance the analysis. This decision was motivated by the alignment of MMR with the research objectives and the precedent set by other studies that successfully used MMR to assess moderators in similar contexts (Ahmed & Sil, 2012). Scholars suggest MMR as an appropriate tool to capture the complexities of such relationships by accounting for the covariances among variables and testing their effects simultaneously (Cheung *et al.*, 2021). This approach allowed for a robust examination of the moderating effects of proactive personality and TSE on the relationship between technostress and IWP while maintaining methodological rigour.

#### 4.10 MULTIVARIATE MULTIPLE REGRESSION ANALYSIS

In this section, the following research objectives will be tested, namely:

- The moderating effect of TSE on IWP constructs at varying levels of technostress.
- The moderating effect of PP on IWP Constructs at varying levels of technostress.

**Figure 4.7** depicts the conceptual framework for addressing the objectives above.

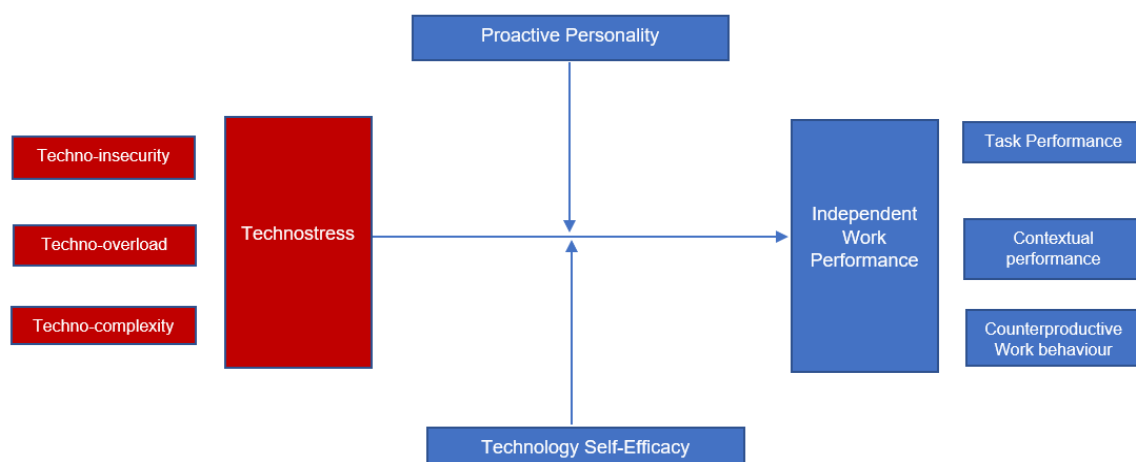


**Figure 4.7: Conceptual model depicting the dimensions of Technostress and IWP with the presence of two moderators**

MMR was used to examine the share and unique influences of independent variable constructs on each dependent variable construct. MMR allows for investigating the unique influences of independent variables on each dependent variable and accounts for potential correlations among dependent variables, thus providing more holistic insights into the relationships between variables (Villa *et al.*, 2003). In the context of this study, we propose that technostress (independent variable) influences IWP (dependent variable). Furthermore, we suggest that this relationship can be moderated through TSE and Proactive Personality. As the literature review chapter states, technostress is a multi-dimensional construct (Chandra *et al.*, 2015) comprising techno-complexity, techno-overload, techno-invasion and techno-uncertainty (Lee, 2021).

#### **4.10.1 Multiple multivariate Regression assumptions**

MMR relies on several assumptions for valid results. Before proceeding to MMR analysis, the researcher needs to ensure that certain assumptions are satisfied (Backhaus *et al.*, 2021);

- Linearity: The relationship between independent and dependent variables should be linear.
- Normality: The residuals (errors) should be normally distributed.
- No Multicollinearity: Independent variables should not be too highly correlated. The researcher needs to conduct a collinearity diagnostic.
- Homoscedasticity: The variance of residuals should remain constant across all levels of the independent variables

All assumptions were checked, indicating that the collected data is fit for MMR analysis.

#### **4.10.2 Effect of TSE on TP at different levels of Techno-insecurity.**

**Table 4.33** presents the analysis results, revealing a clear interaction between TSE and techno-insecurity in predicting TP. Techno-insecurity refers to situations where

workers fear losing their jobs to other workers who can better use ICT (Ragu-Nathan, 2008). Specifically, higher levels of TSE are associated with consistently better task performance, even under varying levels of techno-insecurity. Conversely, TP declines significantly as insecurity increases, irrespective of TSE levels. This pattern highlights the protective role of TSE against the adverse effects of techno-insecurity among academics.

**Table 4.33: Effects of TSE on TP at varying levels of techno-insecurity**

| TSE (effic) | Insecurity (inse) | Predicted Margin | Standard Error | 95% Confidence Interval |          |
|-------------|-------------------|------------------|----------------|-------------------------|----------|
|             |                   |                  |                | Lower                   | Upper    |
| 18          | 5                 | 27.84213         | 5.095527       | 17.81352                | 37.87075 |
| 18          | 15                | 18.94129         | 3.274019       | 12.49762                | 25.38496 |
| 18          | 25                | 10.04045         | 4.514287       | 1.155781                | 18.92511 |
| 23          | 5                 | 29.05592         | 4.328062       | 20.53777                | 37.57407 |
| 23          | 15                | 20.15507         | 1.94683        | 16.32348                | 23.98667 |
| 23          | 25                | 11.25423         | 3.708499       | 3.955456                | 18.55301 |
| 28          | 5                 | 30.2697          | 3.883169       | 22.62715                | 37.91225 |
| 28          | 15                | 21.36886         | 0.6635193      | 20.06297                | 22.67475 |
| 28          | 25                | 12.46802         | 3.272048       | 6.028229                | 18.90781 |
| 33          | 5                 | 31.48349         | 3.873635       | 23.8597                 | 39.10727 |
| 33          | 15                | 22.58265         | 0.8182484      | 20.97223                | 24.19306 |
| 33          | 25                | 13.6818          | 3.352432       | 7.08381,                | 20.2798  |

For individuals with low self-efficacy (effic = 18), TP is highest when insecurity is low (inse = 5), with a predicted margin of 27.84 ( $p < 0.001$ ). However, as insecurity increases to moderate levels (inse = 15), TP declines significantly to 18.94 ( $p < 0.001$ ). When insecurity is high (inse = 25), TP drops further to 10.04 ( $p = 0.027$ ). This demonstrates that individuals with low TSE are particularly vulnerable to techno-insecurity. Among individuals with moderate TSE (effic = 23), TP improves slightly under low insecurity, with a predicted margin of 29.06 ( $p < 0.001$ ). However, performance decreases to 20.16 ( $p < 0.001$ ) under moderate insecurity and further declines to 11.25 ( $p = 0.003$ ) under high insecurity. Although these individuals fare better than those with lower TSE levels, the negative impact of insecurity is still evident.

Individuals with high TSE (effic = 28) exhibit even better TP, achieving a predicted margin of 30.27 ( $p < 0.001$ ) under low insecurity. TP remains relatively strong under moderate insecurity (21.37,  $p < 0.001$ ), but it decreases to 12.47 ( $p < 0.001$ ) under high insecurity. Finally, for individuals with very high TSE (effic = 33), task performance peaks at 31.48 ( $p < 0.001$ ) under low insecurity, declines slightly to 22.58 ( $p < 0.001$ )

under moderate insecurity, and drops further to 13.68 ( $p < 0.001$ ) under high insecurity. These findings suggest that individuals with higher TSE are better equipped to maintain TP under conditions of insecurity, although the adverse effects of high insecurity persist and remain prevalent. As such, these findings highlight the importance of TSE as a buffer against insecurity. While higher levels of TSE mitigate the negative impact of insecurity, TP remains vulnerable to increasing insecurity levels, even for those with strong TSE.

### ***Graphical representation of Predictive margins of Task Performance***

The below graph (**Figure 4.8**) illustrates the relationship between TSE and TP under varying levels of techno-insecurity. The x-axis represents TSE, ranging from 18 to 33 in increments of five, while the y-axis depicts predicted TP scores. The analysis highlights how techno-insecurity moderates the effect of TSE on TP. At low levels of techno-insecurity ( $\text{inse} = 5$ ), represented by the blue line, TP is consistently the highest across all TSE levels. This indicates that individuals experience the least disruption in performance when techno-insecurity is minimal. In contrast, at moderate levels of techno-insecurity ( $\text{inse} = 15$ ), represented by the red line, TP decreases, albeit less severely than under high insecurity conditions. The high levels of insecurity ( $\text{inse} = 25$ ), shown by the green line, result in the most substantial TP decline across all TSE levels.

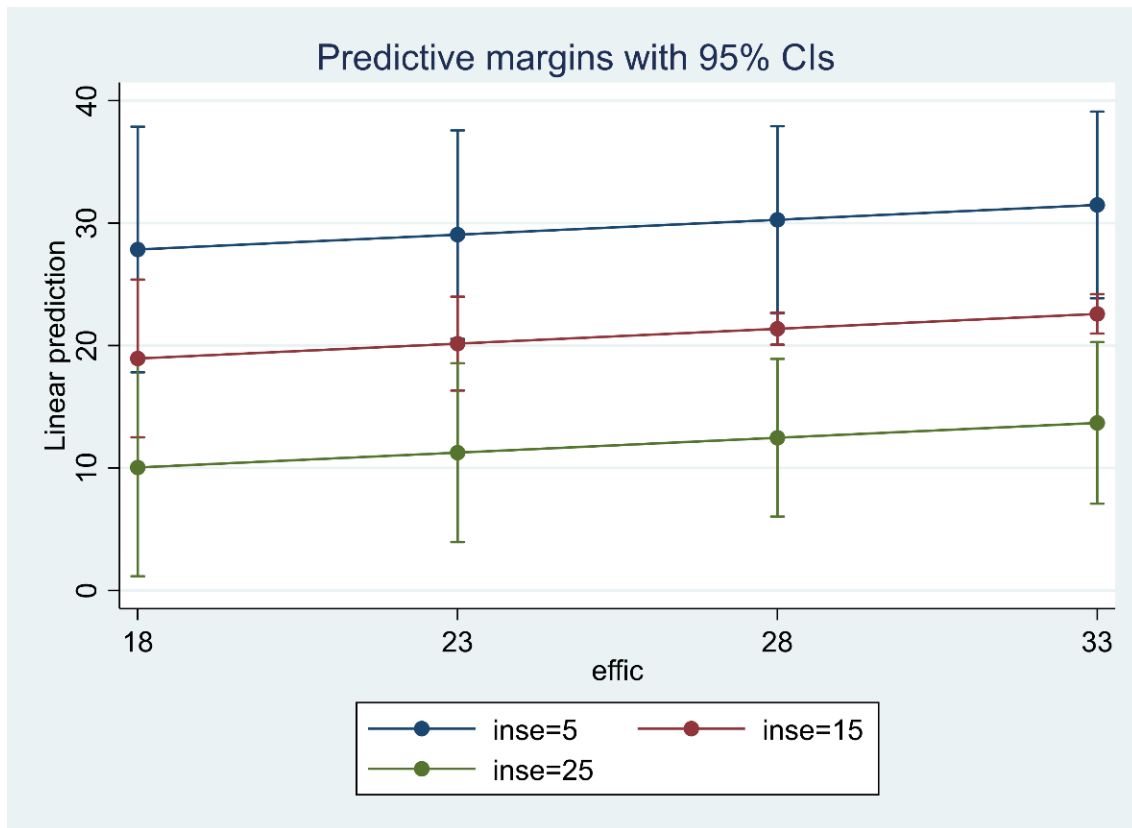


**Figure 4.8: Predictive Margins of TP at Different Levels of TSE and Insecurity**

**Figure 4.8** also demonstrates that TSE positively affects TP across all techno-insecurity conditions. As TSE increases, TP improves, with the gradient of improvement more noticeable under low and moderate insecurity. For instance, individuals with the highest TSE (effic = 33) outperform those with lower TSE (effic = 18) in all insecurity conditions. However, even among individuals with high TSE, TP declines as techno-insecurity increases. The confidence intervals around each point provide insights into the precision of the predictive margins. Wider intervals, particularly under high insecurity conditions (green line), suggest greater variability in TP predictions. This may indicate that high insecurity affects individuals differently, depending on other unmeasured factors. Therefore, these findings underscore the dual role of TSE and insecurity in influencing TP among academic staff members. While TSE acts as a buffer, enabling individuals to maintain higher performance levels, insecurity exerts a negative influence, with greater insecurity leading to steeper declines in TP.

#### 4.10.3 Effect of TSE on TP at different levels of Techno-overload

Continuing with the analysis, we investigated the effect of TSE on TP at different levels of techno-overload, specifically under low, moderate, and high overload conditions. Techno-overload refers to situations where employees are expected to work faster due to ICT usage (Ragu-Nathan, 2008). The findings reveal a consistent pattern where higher TSE improves TP across all levels of techno-overload, with the strength of this relationship varying depending on the degree of overload (**see Table 4.34**).

**Table 4.34: Effect of TSE on TP at varying levels of techno-overload**

| TSE (effic) | Overload (Over) | Predicted Margin | Standard Error | 95% Confidence Interval |          |
|-------------|-----------------|------------------|----------------|-------------------------|----------|
|             |                 |                  |                | Lower                   | Upper    |
| 18          | 6               | 5.287984         | 6.19494        | -6.90441,               | 17.48038 |
| 24          | 6               | 6.744527         | 5.245776       | -3.579797               | 17.06885 |
| 30          | 6               | 8.20107          | 4.670443       | -0.9909293              | 17.39307 |
| 36          | 6               | 9.657612         | 4.611063       | 0.5824799               | 18.73275 |
| 18          | 16              | 12.54176         | 4.173309       | 4.328179                | 20.75534 |
| 24          | 16              | 13.9983          | 2.871245       | 8.347343                | 19.64926 |
| 30          | 16              | 15.45484         | 2.055621       | 11.40913                | 19.50056 |
| 36          | 16              | 16.91139         | 2.315405       | 12.35439                | 21.46838 |
| 18          | 26              | 19.79553         | 3.186581       | 13.52395                | 26.06711 |
| 24          | 26              | 21.25208         | 1.633551       | 18.03705                | 24.4671  |
| 30          | 26              | 22.70862         | 0.580237       | 21.56664                | 23.8506  |
| 36          | 26              | 24.16516         | 1.777316       | 20.66719                | 27.66314 |

As TSE increases, TP gradually improves under low techno-overload conditions (Over = 6). For individuals with low TSE (effic = 18), the predicted TP is 5.29, which is not statistically significant ( $p = 0.394$ ). As TSE increases to 24, performance improves slightly to 6.74, although this result remains statistically non-significant ( $p = 0.200$ ). TP continues to improve for individuals with higher TSE levels, reaching 8.20 at effic = 30 ( $p = 0.080$ ) and 9.66 at effic = 36, which is statistically significant ( $p = 0.037$ ). These results suggest that under conditions of low overload, TSE plays a less pronounced but still meaningful role in enhancing TP.

In contrast, under moderate overload conditions (Over = 16), TSE has a stronger and consistently significant effect on TP. For individuals with low TSE (effic = 18), TP is 12.54, which is statistically significant ( $p = 0.003$ ). Performance improves further as TSE increases, reaching 13.99 at effic = 24 ( $p < 0.001$ ), 15.45 at effic = 30 ( $p < 0.001$ ), and 16.91 at effic = 36 ( $p < 0.001$ ). These findings indicate that TSE is a critical factor in maintaining and enhancing TP under moderate overload.

Under high overload conditions (Over = 26), TSE plays a protective role, enabling individuals to maintain higher TP despite the increased demands. For individuals with low TSE (effic = 18), TP is 19.80 ( $p < 0.001$ ). As TSE increases to 24, performance rises to 21.25 ( $p < 0.001$ ), and at effic = 30, performance improves further to 22.71 ( $p < 0.001$ ). The highest level of TP is observed among individuals with very high self-efficacy (effic = 36), where the predicted margin is 24.17 ( $p < 0.001$ ). These results highlight the robust buffering effect of TSE under high overload conditions.

### ***Graphical representation of Predictive margins of TP***

**Figure 4.9** presents TP's predictive margins across varying TSE and techno-overload levels. The findings reveal a consistent pattern whereby higher TSE is associated with improved TP under all overload levels. Additionally, the effect of overload on TP varies, showing an interesting interaction with TSE levels.

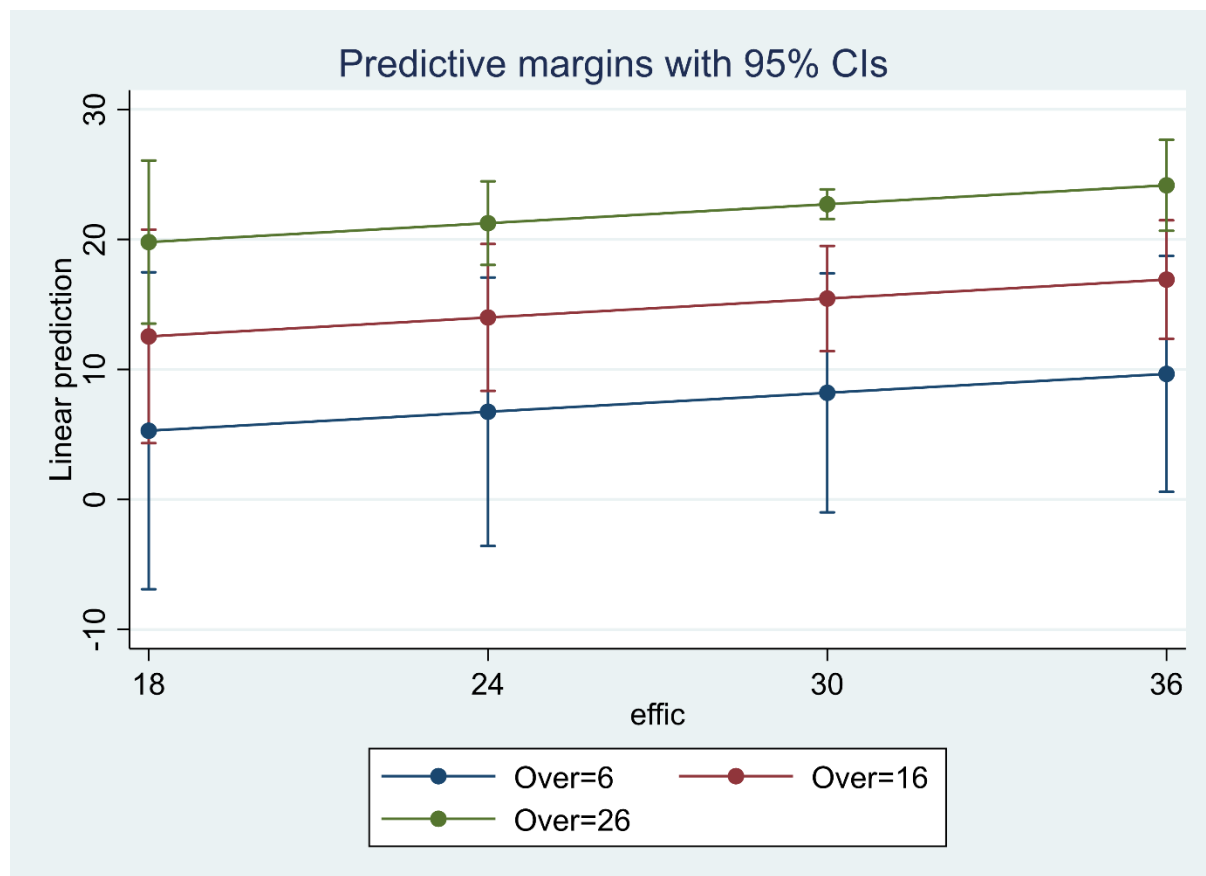


**Figure 4.9: Predictive margins of TP at varying levels of TSE and techno-overload**

At low overload levels (Over = 6), TP gradually increases as TSE rises from  $\text{effic} = 18$  to  $\text{effic} = 36$ . However, the overall predicted margins for TP under low overload conditions are the lowest compared to other overload levels. For instance, at  $\text{effic} = 36$ , TP under low overload is notably lower than TP at the same TSE level under moderate or high overload. The wider confidence intervals for low overload suggest greater prediction variability or uncertainty. Under moderate overload conditions (Over = 16), TP improves significantly as TSE increases. The predicted margins indicate a steady upward trend from low to high TSE, with tighter confidence intervals than low techno-overload, indicating more precise predictions. Moderate techno-overload provides a balanced level of challenge that allows individuals with higher TSE to sustain or improve their performance.

Noticeably, at high overload levels (Over = 26), TP is consistently the highest across all levels of TSE. For individuals with high TSE ( $\text{effic} = 36$ ), TP peaks under high techno-overload conditions. This pattern suggests that individuals with greater TSE may cope with and thrive under challenging conditions, potentially due to adaptive responses, effective coping mechanisms, or increased motivation. The narrower confidence intervals under high overload indicate more consistent TP predictions. These findings underscore the critical role of TSE in maintaining and enhancing TP, even under demanding conditions.

#### **4.10.4 The moderating role of TSE in mitigating CWB under varying levels of Techno-Complexity**

Next, we explored the effect of TSE on Counterproductive Work Behavior (CWB) at varying levels of techno-complexity. Techno-complexity describes situations wherein workers feel it is difficult to learn and use ICT (Ragu-Nathan, 2008). CWB encompasses actions or behaviours detrimental to the organisation (Fox *et al.*, 2012). The results indicate a significant interaction between TSE and techno-complexity, demonstrating that higher TSE mitigates CWB, particularly under low and moderate levels of techno-complexity. However, at high levels of techno-complexity, the relationship between TSE and CWB weakens, with diminishing benefits of TSE in reducing CWB (**see Table 4.35**).

**Table 4.35: Effect of TSE on CWB across different levels of techno-complexity**

| t  | Compl | Proactiveness (Proac) | Predicted Margin | Standard Error | 95% Confidence Interval (Lower) | 95% Confidence Interval (Upper) |
|----|-------|-----------------------|------------------|----------------|---------------------------------|---------------------------------|
| 1  | 5     | 43                    | 47.22356         | 11.5035        | 24.58327                        | 69.86384                        |
| 2  | 5     | 68                    | 38.76076         | 9.793709       | 19.48555                        | 58.03597                        |
| 3  | 5     | 93                    | 30.29796         | 8.834792       | 12.91002                        | 47.6859                         |
| 4  | 5     | 118                   | 21.83516         | 8.87361        | 4.370821                        | 39.29951                        |
| 5  | 15    | 43                    | 34.55079         | 6.586587       | 21.58758                        | 47.51399                        |
| 6  | 15    | 68                    | 26.08799         | 3.697832       | 18.81021                        | 33.36577                        |
| 7  | 15    | 93                    | 17.62519         | 1.586001       | 14.50375                        | 20.74663                        |
| 8  | 15    | 118                   | 9.162393         | 3.14761        | 2.967514                        | 15.35727                        |
| 9  | 25    | 43                    | 21.87801         | 7.744903       | 6.635105                        | 37.12092                        |
| 10 | 25    | 68                    | 13.41522         | 6.081035       | 1.447002                        | 25.38343                        |
| 11 | 25    | 93                    | 4.95242          | 5.703074       | -6.271923                       | 16.17676                        |
| 12 | 25    | 118                   | -3.510378        | 6.828012       | -16.94873                       | 9.927978                        |

At low techno-complexity (Compl = 5), CWB decreases significantly as TSE increases. For individuals with low TSE (effic = 18), the predicted margin for CWB is 47.22 ( $p < 0.001$ ), indicating a high prevalence of counterproductive behaviour. As TSE increases to effic = 24, CWB decreases to 38.76 ( $p < 0.001$ ). For individuals with high TSE (effic = 30 and effic = 36), CWB further reduces to 30.30 ( $p < 0.001$ ) and 21.83 ( $p = 0.014$ ), respectively. These results suggest that under low techno-complexity conditions, TSE minimises counterproductive behaviours.

A similar pattern emerges under moderate techno-complexity (Compl = 15), with CWB decreasing more sharply as TSE increases. For individuals with low TSE (effic = 18), the predicted margin for CWB is 34.55 ( $p < 0.001$ ). As TSE increases to effic = 24, CWB reduces to 26.09 ( $p < 0.001$ ). For individuals with high TSE (effic = 30 and effic = 36), CWB drops to 17.63 ( $p < 0.001$ ) and 9.16 ( $p = 0.004$ ), respectively. These findings indicate that TSE has a stronger mitigating effect on CWB under moderate techno-complexity than low techno-complexity.

At high techno-complexity (Compl = 25), the mitigating effect of TSE on CWB diminishes, with CWB reductions becoming less pronounced or even non-significant. For individuals with low TSE (effic = 18), the predicted margin for CWB is 21.88 ( $p = 0.005$ ). As TSE increases to effic = 24, CWB decreases slightly to 13.42 ( $p = 0.028$ ). However, for individuals with high TSE (effic = 30 and effic = 36), the effect of TSE becomes negligible, with predicted margins for CWB at 4.95 ( $p = 0.386$ ) and -3.51 ( $p = 0.608$ ), respectively. These results suggest that at high levels of techno-complexity, the protective effect of TSE on reducing CWB is limited. As such, these results

highlight the important role of TSE in mitigating CWB under conditions of low and moderate techno-complexity. Higher TSE equips individuals with the confidence and skills needed to navigate technological challenges, thereby reducing counterproductive behaviours. However, at high levels of techno-complexity, even individuals with high TSE may struggle to maintain productive behaviour at work, indicating the need for organisational interventions to address the excessive complexity of technology.

***Graphical representation of predictive margins of TSE and CWB under varying levels of techno-complexity***

**Figure 4.10** illustrates the relationship between TSE and CWB under varying levels of techno-complexity. Notably, CWB consistently decreases as TSE increases, regardless of the level of techno-complexity. This trend underscores the importance of TSE in mitigating the negative effects of technological demands on workplace behaviour.

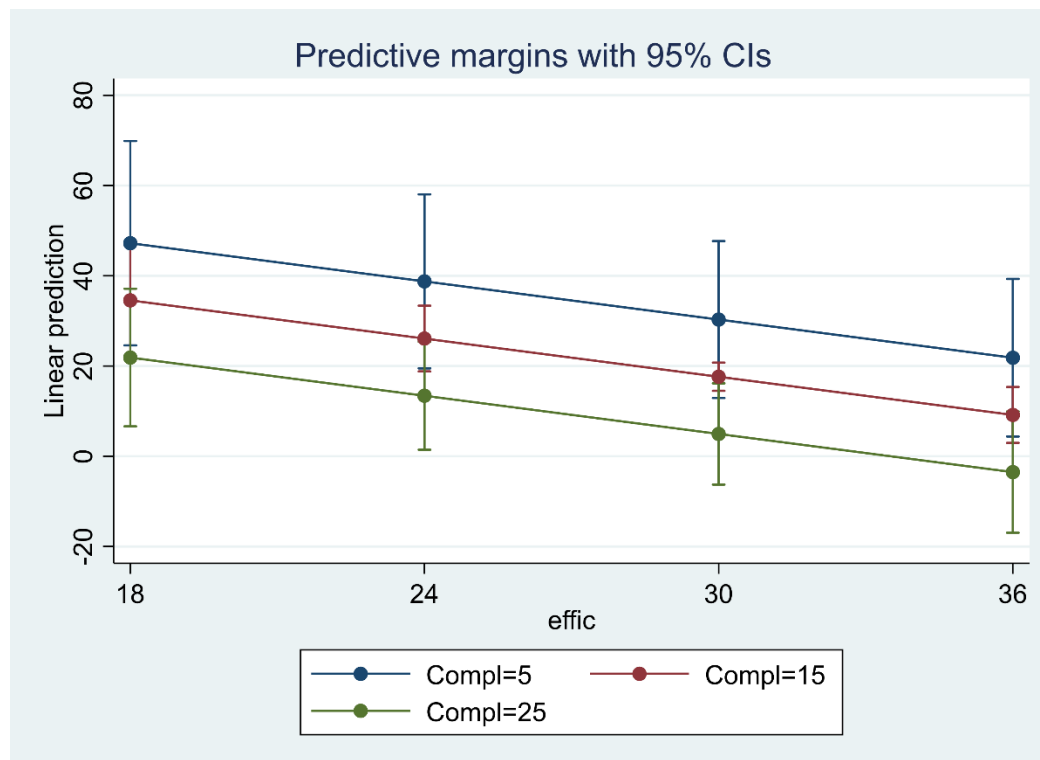


**Figure 4.10: Predictive margins of CWB across levels of TSE and Techno-Complexity.**

At low levels of techno-complexity (Compl = 5), individuals with low TSE (effic = 18) exhibit the highest levels of CWB, with predicted margins declining steadily as TSE increases. For instance, individuals with high TSE (effic = 36) show significantly lower levels of CWB compared to their low TSE counterparts, demonstrating the protective role of TSE even under minimal technological challenges. However, the confidence intervals for low techno-complexity are relatively broad, indicating prediction variability.

Under moderate levels of techno-complexity (Compl = 15), the same pattern of declining CWB with increasing TSE is observed. However, the reduction in CWB is more pronounced than that of low techno-complexity. Individuals with low TSE (effic = 18) exhibit higher CWB than those with moderate or high TSE (effic = 30 or effic = 36), suggesting that TSE plays a stronger mitigating role as techno-complexity increases. At high levels of techno-complexity (Compl = 25), the effect of TSE on CWB is most significant. Individuals with low TSE (effic = 18) still exhibit elevated levels of CWB, but as TSE increases, CWB declines steeply. By effic = 36, the predicted margins for CWB are minimal, indicating that individuals with high TSE are better equipped to manage the challenges posed by high techno-complexity. The confidence intervals under high techno-complexity are narrower, reflecting greater prediction consistency. Overall, the above findings demonstrate that TSE serves as a critical buffer against CWB, particularly under higher levels of techno-complexity. While low TSE is associated with elevated CWB across all complexity levels, high TSE significantly reduces CWB and enables individuals to adapt to complex technological environments.

#### **4.10.5 Effect of proactiveness on Contextual Performance at different levels of Techno-Complexity**

In further analysis, the researcher then examined the relationship between proactiveness (Proactive Personality) and Contextual Performance (CP) under varying levels of techno-complexity. The findings demonstrate a consistent trend: Higher levels of proactiveness are associated with improved CP across all levels of techno-complexity. However, the extent of this improvement varies depending on the complexity of the technological environment. Table 4.36 summarises the moderative effects of proactiveness on CP.

**Table 4.36: Effect of Proactiveness on CP at varying Levels of Techno-Complexity**

| Proactiveness (Proac) | Techno-Complexity (Compl) | Predicted Margin | Standard Error | 95% Confidence Interval | 95% Confidence Interval |
|-----------------------|---------------------------|------------------|----------------|-------------------------|-------------------------|
|                       |                           |                  |                | (Lower)                 | (Upper)                 |
| 43                    | 5                         | 30.64637         | 10.45179       | 10.07597                | 51.21677                |
| 68                    | 5                         | 40.18865         | 8.13928        | 24.16955                | 56.20774                |
| 93                    | 5                         | 49.73092         | 6.936839       | 36.07838                | 63.38346                |
| 118                   | 5                         | 59.2732          | 7.406454       | 44.6964                 | 73.85                   |
| 43                    | 15                        | 16.05875         | 7.248385       | 1.793048                | 30.32445                |
| 68                    | 15                        | 25.60103         | 3.821642       | 18.07957                | 33.12248                |
| 93                    | 15                        | 35.1433          | 1.238856       | 32.70508                | 37.58152                |
| 118                   | 15                        | 44.68558         | 3.650828       | 37.50031                | 51.87085                |
| 43                    | 25                        | 1.471132         | 7.822837       | -13.92516               | 16.86743                |
| 68                    | 25                        | 11.01341         | 5.32171        | 0.539637                | 21.48718                |
| 93                    | 25                        | 20.55568         | 4.506481       | 11.68638                | 29.42498                |
| 118                   | 25                        | 30.09796         | 6.095909       | 18.10047                | 42.09545                |

At low techno-complexity (Compl = 5), CP increases significantly with the increase in proactiveness among the individuals. Individuals with low proactiveness (proac = 43) exhibit a predicted CP of 30.65 ( $p = 0.004$ ), which improves substantially as proactiveness increases. For instance, at moderate proactiveness (proac = 68), CP rises to 40.19 ( $p < 0.001$ ). Similarly, for individuals with high proactiveness (proac = 93 and proac = 118), CP improves to 49.73 ( $p < 0.001$ ) and 59.27 ( $p < 0.001$ ), respectively. These results indicate that proactiveness plays a significant role in enhancing CP in environments with minimal technological complexity.

The same pattern emerges under moderate techno-complexity (Compl = 15), although the baseline performance is slightly lower compared to low techno-complexity. At low proactiveness (proac = 43), CP is 16.06 ( $p = 0.027$ ). As proactiveness increases to proac = 68, performance improves significantly to 25.60 ( $p < 0.001$ ). For individuals with high proactiveness (proac = 93 and proac = 118), performance reaches 35.14 ( $p < 0.001$ ) and 44.69 ( $p < 0.001$ ), respectively. These findings suggest that while moderate techno-complexity slightly dampens CP, higher levels of proactiveness mitigate this effect.

At high techno-complexity (Compl = 25), the relationship between proactiveness and CP becomes less pronounced at lower levels of proactiveness. For instance, individuals with low proactiveness (proac = 43) exhibit a predicted performance of 1.47, which is not statistically significant ( $p = 0.851$ ). However, as proactiveness

increases, performance improves substantially. At moderate proactiveness (proac = 68), performance rises to 11.01 ( $p = 0.039$ ), and at high proactiveness (proac = 93 and proac = 118), it increases to 20.56 ( $p < 0.001$ ) and 30.10 ( $p < 0.001$ ), respectively. These results indicate that at high levels of techno-complexity, only individuals with higher proactiveness can maintain or improve their contextual performance. Across all levels of techno-complexity, higher proactiveness is associated with improved CP. The effect of proactiveness is strongest under low and moderate techno-complexity, where individuals can leverage their proactive behaviours more effectively.

### ***Graphical representation of the Influence of Proactiveness on CP across varying levels of Techno-Complexity***

The following section examines the relationship between Proactive Personality (proactiveness) and contextual performance in environments characterised by varying levels of techno-complexity. Proactive personality, which is defined as an individual's tendency to anticipate and take initiative in addressing challenges, is expected to positively influence contextual performance, particularly in complex technological environments (McCormick *et al.*, 2019) and is hypothesised to moderate this relationship. Techno-complexity, a sub-construct of Technostress, reflects the difficulty and intricacy of using technology in the workplace. **Figure 4.11** illustrates the predictive margins of CP across varying levels of proactiveness (proac) and techno-complexity (Compl). According to the findings, there is a consistent positive relationship between proactiveness and CP across all levels of techno-complexity. As proactiveness increases, CP improves, with the steepest gains observed under low techno-complexity (Compl = 5). For individuals with low proactiveness (proac = 43), CP is lowest across all techno-complexity levels. However, as proactiveness rises to higher levels (proac = 93 and proac = 118), CP improves significantly, regardless of the complexity of the technological environment.

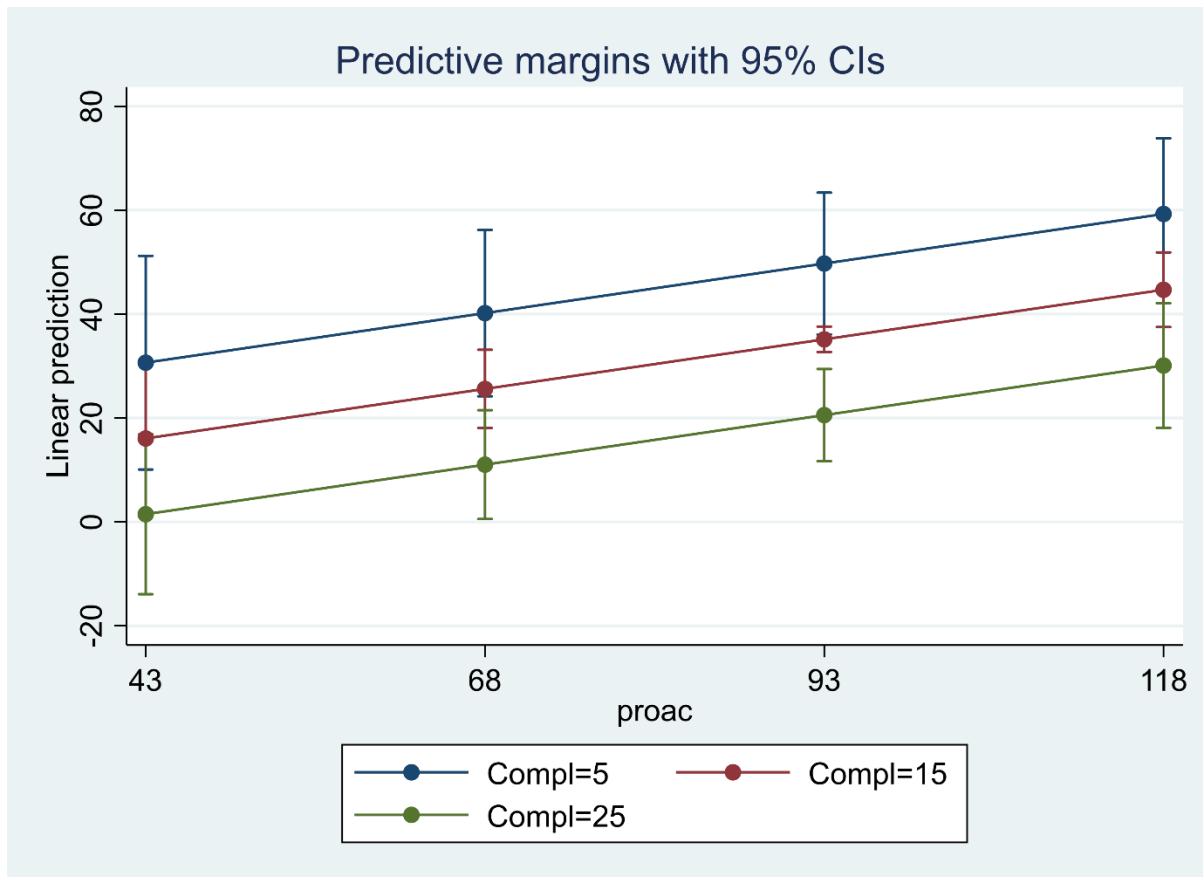


**Figure 4.11: Predictive Margins of CP across levels of Proactiveness and Techno-Complexity.**

The results further demonstrate that techno-complexity moderates the effect of proactiveness on CP. At low levels of techno-complexity (Compl = 5), CP is highest, with steeper gains observed as proactiveness increases. In contrast, at moderate techno-complexity (Compl = 15), CP rises more gradually, reflecting a smaller but still significant effect of proactiveness. At high techno-complexity (Compl = 25), the effect of proactiveness on CP is the weakest, though still statistically significant, as shown by the flatter slope of the green line. This suggests that while proactiveness contributes to improved performance under all conditions, its impact is more pronounced in simpler technological environments and diminishes as the complexity of tasks increases. These findings highlight the importance of fostering proactiveness to sustain CP, especially in environments with varying technological demands.

#### 4.11 HYPOTHESES DECISIONS

**Table 4.37** summarises the research objectives, hypotheses, and decisions related to each hypothesis, as this chapter addresses.

| Secondary Objectives                                                                                                                                                                                                    | Hypotheses                                                                                                                                                                                                                                                                  | Outcome   |
|-------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|-----------|
| To develop a framework to assess the influence of technostress on academic staff's performance and the moderating role of technology self-efficacy and proactive personality in a selected higher education institution | <b>H<sub>01</sub>:</b> A framework cannot be developed to explain how technostress influences academic staff's performance and how technology self-efficacy and proactive personality moderate this relationship.                                                           | Rejected  |
|                                                                                                                                                                                                                         | <b>Ha<sub>1</sub>:</b> A framework can be developed to explain how technostress influences academic staff's performance and how technology self-efficacy and proactive personality moderate this relationship.                                                              | Accepted  |
| To establish the means scores of technostress, individual work performance, technological self-efficacy and proactive personality of academic staff.                                                                    | <b>H<sub>02</sub>:</b> The mean scores of technostress, individual work performance, technological self-efficacy, and proactive personality among academic staff in the selected higher education institution do not significantly differ from expected or baseline values. | Rejected  |
|                                                                                                                                                                                                                         | <b>Ha<sub>2</sub>:</b> The mean scores of technostress, individual work performance, technological self-efficacy, and proactive personality among academic staff in the selected higher education institution significantly differ from expected or baseline values.        | Supported |
| To establish if there are differences in technostress, individual work performance, technological self-efficacy and proactive personality between genders.                                                              | <b>H<sub>03</sub>:</b> There are no significant differences in technostress, individual work performance, technological self-efficacy, and proactive personality among academic staff gender groups.                                                                        | Rejected  |
|                                                                                                                                                                                                                         | <b>Ha<sub>3</sub>:</b> There are significant differences in technostress, individual work performance, technological self-efficacy, and proactive personality among academic staff gender groups.                                                                           | Supported |
| To establish if there are differences in technostress, individual work performance, technological self-efficacy and proactive personality between age groups.                                                           | <b>H<sub>04</sub>:</b> There are no significant differences in technostress, individual work performance, technological self-efficacy, and proactive personality across age groups among academic staff.                                                                    | Rejected  |
|                                                                                                                                                                                                                         | <b>Ha<sub>4</sub>:</b> Among academic staff, there are significant differences in technostress, individual work performance, technological self-efficacy, and proactive personality across age groups.                                                                      | Supported |
| To establish if there is a relationship between technostress and individual work performance.                                                                                                                           | <b>H<sub>05</sub>:</b> Technostress and individual work performance among academic staff do not significantly correlate.                                                                                                                                                    | Rejected  |
|                                                                                                                                                                                                                         | <b>Ha<sub>5</sub>:</b> Technostress and individual work performance among academic staff are significantly related.                                                                                                                                                         | Supported |

|                                                                                                                                                                |                                                                                                                                            |           |
|----------------------------------------------------------------------------------------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------------------|-----------|
| To assess the moderating role of technology self-efficacy and proactive personality in the relationship between technostress and academic staff's performance. | <b>H<sub>06</sub></b> : Technology self-efficacy does not moderate the relationship between technostress and academic staff's performance. | Rejected  |
|                                                                                                                                                                | <b>Ha<sub>6</sub></b> : Technology self-efficacy moderates the relationship between technostress and academic staff's performance.         | Supported |
| To assess the moderating role of proactive personality in the relationship between technostress and academic staff's performance.                              | <b>H<sub>07</sub></b> : Proactive personality does not moderate the relationship between technostress and academic staff's performance.    | Rejected  |
|                                                                                                                                                                | <b>Ha<sub>7</sub></b> : Proactive personality moderates the relationship between technostress and academic staff's performance             | Supported |

#### 4.10 SUMMARY

This chapter addressed the research findings of this study. A demographic description of the sample was presented, revealing a fair representation of males and females who took part in the study. Most respondents were aged 30-50 years old. Descriptive statistics were also presented, revealing that academic staff members agreed with how technostress influences work performance. The scales were tested using factor analysis and CFA, and the results indicated a good model fit and allowed for the reduction of items for the remainder of the study. To address the research objectives, the following statistical analyses were performed: an MMR regression analysis was conducted to determine the influence of technostress on academic staff performance. Furthermore, regression analysis was undertaken to determine the moderative effects of proactive personality and technology self-efficacy. The regression analysis showed that TSE significantly affected the prevalence of technostress among academic staff.

## **CHAPTER 5**

### **DISCUSSION OF FINDINGS, CONCLUSIONS AND RECOMMENDATIONS**

#### **5.1 INTRODUCTION**

This chapter offers a comprehensive overview of the study, summarising the key findings related to the primary research objective: to develop a framework for assessing the influence of technostress on academics' individual performance in a selected higher education institution. The chapter begins by outlining the conclusions drawn from the findings related to the established research objectives. Following this, it presents recommendations informed by these insights. Additionally, the chapter addresses the limitations encountered throughout the research process and concludes with suggestions for future studies in this research area.

#### **5.2 DISCUSSION OF THE RESULTS**

The primary objective of this study was to develop a framework to assess the influence of technostress on academics' IWP at a selected higher education institution. The study also explored whether proactive personality (PP) and technology self-efficacy (TSE) moderated this relationship. This section presents conclusions on the secondary objectives and hypotheses.

The findings are compared with results from similar studies in this field. Furthermore, the section also discusses the implications of the findings and makes recommendations for policymakers and stakeholders involved in higher education, outlining the policies to adopt and implement when introducing educational technology in this space.

### 5.2.1 Discussion of the integrated framework

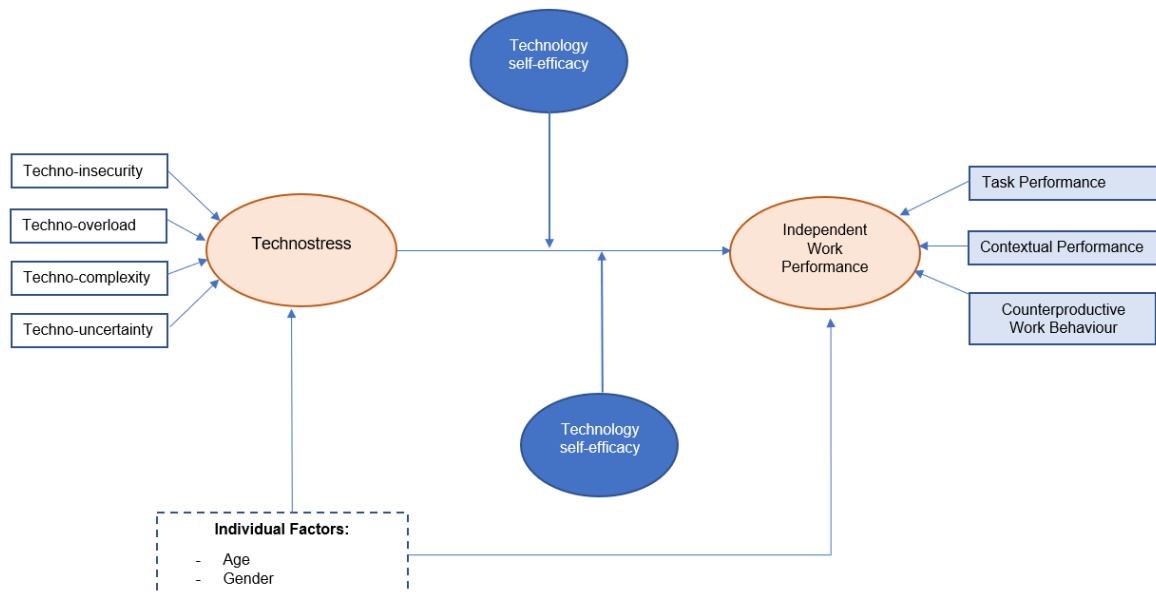


**Figure 5.1: Final conceptualised integrated framework based on the analysis**

The primary research objective was to develop a framework for assessing the influence of technostress on the performance of academic staff, as well as the moderating roles of TSE and PP, within a selected higher education institution. An integrated framework (Figure 5.1) was developed depicting the variables under investigation and conceptualising the influence of technostress on academic staff performance, taking into account the moderating roles of TSE and PP within higher education institutions. This framework examines the direct relationship between technostress (encompassing techno-overload, techno-complexity, techno-insecurity and techno-uncertainty) and IWP (comprising task performance, contextual performance and counterproductive work behaviour). Additionally, the moderating influences of technological self-efficacy and PP on this relationship are explored, proposing that individuals with higher self-efficacy and proactive traits are better able to mitigate the negative impact of technostress on their work performance.

The framework was developed through a structured methodological approach. Initially, a comprehensive literature review identified the key constructs (technostress, IWP, TSE, PP) and their theoretical interrelationships. Based on the literature review, the study developed specific hypotheses to examine relationships and moderation effects

among the variables. The framework proposes that technostress affects individual work performance across task performance, contextual performance and counterproductive work behaviours. It further posits that technology self-efficacy and proactive personality moderate this relationship. Higher levels of these moderators reduce the adverse effects of technostress (Tarafdar *et al.*, 2019; Ayyagari *et al.*, 2011; Tiwari, 2021; Koopmans *et al.*, 2014). In the final specification, technostress is the independent variable, individual work performance is the dependent variable and technology self-efficacy and proactive personality act as moderators (Wang & Li, 2019; Hung *et al.*, 2015).

Descriptive statistics (mean, standard deviation, minimum, maximum) were computed for each variable to establish baselines and confirm construct levels within the sample (Koopmans *et al.*, 2014; Gentry *et al.*, 2014; Bateman & Crant, 1993; Tarafdar *et al.*, 2007). Group differences by gender and age were tested with the Kruskal–Wallis test and the Mann–Whitney U test to examine demographic variation in technostress and the moderators (Field, 2013). Age-related differences were probed with Kruskal–Wallis and Dunn’s pairwise comparisons with Bonferroni adjustment to clarify how age shaped the constructs (Field, 2013). Spearman’s rank correlations assessed associations between technostress and individual work performance dimensions, showing a significant negative relationship consistent with theory (Tarafdar *et al.*, 2019; Koopmans *et al.*, 2014).

Moderation by technology self-efficacy was tested with multivariate multiple regression models that included interaction terms (technostress  $\times$  TSE). Significant interactions indicated that higher technology self-efficacy attenuated the negative impact of technostress on performance outcomes (Hair *et al.*, 2014; Tarafdar *et al.*, 2011; Wang *et al.*, 2004). The moderating role of proactive personality was examined with the same approach. Prior evidence reported a strong technostress  $\times$  proactive personality effect, indicating reduced adverse impacts at higher levels of proactivity (Hung *et al.*, 2015; Tiwari, 2020; Tiwari, 2021). An alternative structural model was also considered. Structural equation modelling was employed to test this model empirically. However, the results indicated mixed outcomes regarding model fit. Several goodness-of-fit indices were applied to evaluate how well the proposed theoretical model aligned with the observed data. The overall fit of the tested model demonstrated some strengths

but ultimately proved suboptimal. The Chi-square statistic yielded a value within an acceptable range ( $\chi^2 = 4.335$ , within the recommended range of 3–5), suggesting an acceptable absolute fit. Additionally, the root mean square error of approximation (RMSEA) was 0.069, indicating an acceptable fit within the generally acceptable range of 0.06–0.08. However, significant shortcomings were apparent with other fit indices. The comparative fit index (CFI = 0.691) and the Tucker–Lewis index (TLI = 0.673) were below the acceptable threshold of 0.90, indicating that the relative fit of the proposed model was poor. Similarly, the goodness-of-fit index (GFI = 0.79) also fell below the accepted threshold of 0.90, confirming the suboptimal fit of the proposed model, as did the likelihood ratio tests. The chi-square test comparing the model with the saturated model yielded significant differences ( $\chi^2 = 4658.314$ ,  $p < 0.001$ ), indicating that the hypothesised model did not capture the data structure perfectly. This result, however, is often expected in practical applications due to the sensitivity of chi-square to large sample sizes ( $n = 304$ ) and complex model specifications.

To enhance the model's fit, further adjustments were made by removing items with factor loadings below 0.5, aiming to strengthen the robustness of the latent constructs. Despite these refinements, indices such as the CFI (0.723) and TLI (0.705) remained below acceptable thresholds, still highlighting areas for further structural refinement. Nonetheless, some metrics, such as RMSEA (0.067) and standardised root mean squared residual (SRMR = 0.075), indicated a reasonable to good fit, demonstrating that while the model had theoretical relevance, it required additional optimisation.

Given these mixed findings, the study recognised limitations in the SEM approach. Subsequently, it recommended considering alternative analytical methods, such as multivariate multiple regression (MMR), to better capture the complexity of the relationships among the examined variables. Overall, the model tested in this study demonstrated a partial fit to the data, suggesting the need for further theoretical and methodological refinements in future research.

### **Hypothesis 1:**

- $H_{01}$ : A framework cannot be developed to explain how technostress influences the performance of academic staff and how TSE and PP moderate this relationship.
- $H_{a1}$ : A framework can be developed to explain how technostress influences the performance of academic staff and how TSE and PP moderate this relationship.

The null hypothesis ( $H_{01}$ ) was rejected, and the alternative hypothesis ( $H_{a1}$ ) was accepted.

### **5.2.2 Discussion of the mean scores of technostress, individual work performance, technological self-efficacy and proactive personality of academic staff**

Research objective two was to establish the mean scores of technostress, IWP, technological self-efficacy and PP of academic staff. The findings from the present study on technostress, IWP, technological self-efficacy (TSE) and PP among academic staff align with prior research in the literature. The observed mean technostress scores (ranging from  $M = 2.65$  to  $M = 4.43$ ) indicate moderate to high stress levels experienced by academics, mainly due to techno-overload and techno-invasion. This finding aligns closely with prior research, notably that of Chen (2015), who also reported moderate technostress levels (overall  $M = 2.95$ ,  $SD = 0.57$ ). Chen identified techno-overload ( $M = 3.24$ ,  $SD = 0.80$ ) as a significant source of technostress. Chen's (2015) findings confirm that workload pressures and uncertainty driven by technological demands strongly affect professionals.

The current results underscore that academics experience significant cognitive and emotional strain due to the constant connectivity and technological demands. This finding aligns with Aktan and Toraman's (2022) study, which found that heightened technostress resulting from intensive technology use had a negative impact on job performance. Similarly, Arslan *et al.* (2022) confirmed elevated technostress among teachers transitioning to digital teaching during COVID-19, further validating the present study's findings of notable technostress in educational contexts.

Regarding individual work performance, the results showed high contextual performance. Mean scores ranged from 3.82 to 4.23. This pattern indicates active engagement in voluntary behaviours that benefit the institution. These levels differ from those reported by Koopmans *et al.* (2014), who found lower contextual performance,  $M = 2.31$ ,  $SD = 0.77$ . The difference likely reflects distinct organisational

cultures and job expectations among academic staff and the professional groups examined by Koopmans *et al.* (2014). The study also reported low counterproductive work behaviour. For example, CWB3 recorded a mean of 2.61. This aligns with Koopmans *et al.*'s results (CWB:  $M = 1.11$ ,  $SD = 0.67$ ), confirming limited negative behaviours among professionals.

Regarding technological self-efficacy, the consistently high scores (TSE:  $M = 4.78$  to  $M = 5.38$ ) among academic staff indicate robust confidence in adapting to and using technology effectively. This finding aligns with the results of Kent and Giles (2017), who reported a high level of technological self-efficacy (overall  $M = 4.6$ ), particularly in integrating technology into professional tasks. This high level of self-efficacy is likely to buffer the impact of technostress and enhance the academic staff's adaptability to technological demands.

Findings on PP, with scores ranging from  $M = 4.68$  to  $M = 6.10$ , indicate that academics exhibited a strong tendency towards initiative and proactive behaviours. These findings parallel the research of Bateman and Crant (1993), who reported high PP levels ( $M = 90.7$ ,  $SD = 11.4$ ) and confirmed their validity in predicting proactive workplace behaviours. However, the lower mean score for initiating long-term strategic actions (PPS13:  $M = 4.68$ ) suggests variability among staff regarding strategic proactive behaviours, indicating areas for further development or targeted organisational support.

The empirical literature thus supports and expands upon the current findings, highlighting broader recognition of technostress as a widespread issue, as well as the strong self-efficacy and proactive tendencies among academic staff and the crucial role these factors play in shaping workplace behaviours and performance outcomes (Arslan *et al.*, 2022; Chen, 2015; Kent & Giles, 2017; Koopmans *et al.*, 2014). Such integration emphasises the necessity for institutional strategies to mitigate technostress and foster adaptive capabilities among academic professionals.

## **Hypothesis 2:**

- $H_{02}$ : The mean scores of technostress, IWP, technological self-efficacy and PP among academic staff in the selected higher education institution do not significantly differ from expected or baseline values.
- $H_{a2}$ : The mean scores of technostress, IWP, technological self-efficacy and PP among academic staff in the selected higher education institution differ significantly from the expected or baseline values.

The null hypothesis ( $H_{02}$ ) was rejected, and the alternative hypothesis ( $H_{a2}$ ) was supported.

### **5.2.3 Discussion of differences in technostress, individual work performance, technological self-efficacy and proactive personality between genders**

Research objective three was to establish whether there were differences in technostress, IWP, TSE and PP between genders. Research findings indicated apparent gender differences in technostress levels among academic staff, aligning closely with existing literature. The current study found a significant difference in technostress between male and female academic staff ( $\chi^2 = 3.887$ ,  $p = 0.0487$ ), with male staff reporting higher levels of technostress. This outcome aligns with prior research suggesting that men often experience higher levels of techno-overload and techno-invasion, possibly due to heightened sensitivity to achievement-related stress associated with technology use (Marchiori *et al.*, 2019; Leitner & Rašticová, 2024; Riedl *et al.*, 2013). Conversely, previous studies frequently reported higher overall technostress among women, particularly concerning techno-complexity and techno-uncertainty (Leitner & Rašticová, 2024; Marchiori *et al.*, 2019). Agbu and Simeon (2011) found no significant gender differences in technostress experiences. This highlights how technostress varies by context and culture rather than being solely a function of gender. In the current study, no significant gender differences were observed in the IWP dimensions: task performance, contextual performance or counterproductive work behaviours. Male and female academic staff performed similarly in these areas. This result contrasts somewhat with existing research, which often reports gender-based differences. For example, Crews and Russ (2020) found that women multitasked more effectively. Park (2020) noted the organisational benefits of balanced gender representation. Yet the current findings align with Casu *et al.*

(2021), who reported that job satisfaction impacted task performance equally across genders.

Regarding TSE, the results showed no significant differences in gender. Male and female academic staff were equally confident using technology. This aligns with the findings of Šabić *et al.* (2021), who noted minimal gender differences among younger educators, although these differences increased with age. Woods *et al.* (2021) and Huffman *et al.* (2013) argue that gender roles and generational factors influence self-efficacy more than biological sex alone. This emphasises the complexity of technological confidence.

Finally, the study found no gender differences in PP. Male and female academic staff displayed similar levels of proactivity. This finding supports the existing literature, which suggests that PP generally transcends gender. However, variations linked to age and career stage have been observed (Zacher, 2012; Zacher & Bock, 2014). Bohlmann and Zacher (2020) further suggest that age and gender interactions influence perceptions of proactive behaviour. Still, such interactions were not evident among academic staff in this study, suggesting consistent proactive behaviours across genders.

### **Hypothesis 3:**

- $H_{03}$ : There are no significant differences in technostress, IWP, TSE and PP among academic staff gender groups.
- $H_{a3}$ : There are significant differences in technostress, IWP, TSE and PP among academic staff gender groups.

The null hypothesis ( $H_{03}$ ) was rejected, and the alternative hypothesis ( $H_{a3}$ ) was supported.

#### **5.2.4 Discussion of differences in technostress, individual work performance, technology self-efficacy and proactive personality between age groups**

Research objective four was to determine if there were differences in technostress, IWP, technological self-efficacy and PP among age groups. The results indicated no significant age differences in technostress. However, specific stressors, such as techno-complexity and techno-insecurity, were higher among older groups (50–59).

This aligns with prior research, which found that older employees generally experienced greater techno-complexity and uncertainty (Setyadi *et al.*, 2017; Leitner & Rašticová, 2024). Younger academics (18–29) displayed greater technological confidence, a finding that aligns with McCoy's (2010) research and highlights higher levels of technology proficiency in younger age groups.

Younger academics exhibited lower levels of task and contextual performance, contrasting with prior findings that older employees often demonstrated greater engagement and dedication (Roberts, 2020; Roy, 2022). Mid-career staff (40–49 years old) exhibited increased counterproductive behaviours, diverging from existing literature that suggests age diversity has a positive impact on organisational performance (Beier *et al.*, 2022).

Higher TSE among younger staff aligns with findings in the literature, which indicate that younger generations tend to report higher levels of technological proficiency (McCoy, 2010). Age significantly influences TSE and training outcomes, with older women often benefiting more from training than older men (Bausch *et al.*, 2014).

Younger staff exhibited higher PP scores, consistent with research indicating stronger proactive traits and training outcomes in younger individuals (Bertolino *et al.*, 2011). Mid-career staff exhibiting lower PP contrasts with the literature, which highlights the positive association between proactivity and job search intensity among older workers (Zacher, 2012; Zacher & Bock, 2014).

#### **Hypothesis 4:**

- $H_{04}$ : There are no significant differences in technostress, IWP, technological self-efficacy and PP among academic staff across age groups.
- $H_{a4}$ : Among academic staff, significant differences exist in technostress, IWP, technological self-efficacy and PP across age groups.

The null hypothesis ( $H_{04}$ ) was rejected, and the alternative hypothesis ( $H_{a4}$ ) was supported.

#### **5.2.5 Discussion of the relationship between technostress and individual work performance**

Research objective five was to determine if a relationship existed between technostress and IWP. In this section, the conclusions for research objective five are presented. This study found a strong negative relationship between technostress and IWP among academic staff, as shown by a Spearman's rho of -0.85 ( $p < 0.007$ ). This suggests that as technostress increased, employee performance significantly declined. High technostress negatively impacts job performance due to constant technological disruptions and information overload (Ayyagari *et al.*, 2011; Tarafdar *et al.*, 2019). Specifically, academics face increased challenges in adapting to technological demands, reducing their effectiveness (Jena, 2015; Govender & Mpungose, 2022). According to Bourlakis, Nisar and Prabhakar (2023), technostress has been associated with decreased work performance in the higher education sector. Additionally, research consistently shows that technostress has a significant impact on work performance. Multiple studies have found negative relationships between technostress and job performance (Gerdiken, Reinwald & Kunze, 2021). Furthermore, technostress has been linked to decreased productivity, diminished job satisfaction and increased turnover intention (Gerdiken *et al.*, 2021), corroborating the findings of this study.

#### **Hypothesis 5:**

- $H_{05}$ : Technostress and IWP among academic staff do not significantly correlate.
- $H_{a5}$ : Technostress and IWP among academic staff are significantly related.

The null hypothesis ( $H_{05}$ ) was rejected, and the alternative hypothesis ( $H_{a5}$ ) was accepted. This indicates a significant relationship between technostress and IWP among academic staff.

#### **5.2.6 Discussion of the moderating role of technology self-efficacy in the relationship between technostress and academic staff performance**

Research objective six was to assess the moderating role of TSE in the relationship between technostress and academic staff performance. To achieve this objective, MMR was used to test the interaction between TSE and techno-insecurity in predicting task performance. Digital technologies are now essential for teaching, research and administration in higher education institutions. Moreover, the increased use of ICT brings psychological challenges, known as technostress. Technostress refers to the

stress caused by using or interacting with technology, negatively impacting work performance (Tarafdar *et al.*, 2014; Tiwari, 2020). Identifying factors that reduce the negative impacts of technostress has become essential for researchers. One key factor is TSE, defined as the belief in one's ability to use technology effectively (Kulviwat, Bruner II & Neelankavil, 2014). TSE shapes how academic staff respond to technology-related stress. Data show a significant interaction between TSE and technostress dimensions, such as techno-insecurity and techno-overload, in predicting task performance. Individuals with higher TSE exhibited better task performance at all techno-insecurity levels compared to those with lower TSE. For example, staff with a very high TSE score (33) achieved a task performance score of 31.48 under low insecurity, compared to 13.68 under high insecurity. In contrast, those with low TSE (efficacy = 18) experienced a more drastic drop in performance, from 27.84 to 10.04 across the same insecurity levels. These results suggest that high TSE serves as a psychological buffer, mitigating the perceived threat of job-related insecurity associated with technological advancements (Ragu-Nathan *et al.*, 2008).

Similarly, TSE significantly enhanced task performance under varying degrees of techno-overload. While under low overload, the effect of TSE was moderate; its influence became pronounced as overload increased. Under high overload conditions, individuals with high TSE maintained the highest levels of task performance, with a predicted margin of 24.17 for efficacy of 36, highlighting the resilience of high self-efficacy. These findings support the theoretical proposition that TSE enables individuals to approach challenging ICT demands with confidence and control, thereby minimising their adverse effects on performance (Kim & Lee, 2021).

However, the moderating effect of TSE appears less robust when CWB is examined under conditions of high techno-complexity. Although higher TSE consistently corresponded with reduced CWB under low and moderate complexity, the mitigating effect diminished at high complexity levels. For instance, individuals with very high TSE showed a slight advantage over those with lower TSE in curbing CWB under high techno-complexity. This suggests that when technological systems become excessively complex or cognitively demanding, even individuals with high self-efficacy may face challenges in adapting effectively, resulting in diminished performance and possible engagement in unproductive behaviours (Fox *et al.*, 2012).

These findings are consistent with prior empirical and theoretical work. Marchiori, Mainardes and Rodrigues (2019) concluded that TSE moderated the negative relationship between technostress and job performance. Their study indicated that individuals with high TSE were more likely to interpret technostress as a challenge rather than a threat. Similarly, Shu, Tu and Wang (2011), drawing on Social Cognitive Theory, demonstrated that employees with high computer self-efficacy reported significantly lower levels of technostress. Andreou (2019), in a qualitative study of employees in a technology-intensive environment, found that perceived self-efficacy substantially influenced the extent to which technostress impacted performance.

### **Hypothesis 6:**

- $H_{06}$ : TSE does not moderate the relationship between technostress and academic staff performance.
- $H_{a6}$ : TSE moderates the relationship between technostress and academic staff performance.

The null hypothesis ( $H_{06}$ ) was rejected, supporting the alternative hypothesis ( $H_{a6}$ ). This means TSE significantly moderated the relationship between technostress and academic staff performance, serving as a buffer against the negative impacts of technostress.

### **5.2.7 Discussion of the moderating role of proactive personality in the relationship between technostress and academic staff performance**

Research objective seven was to assess the moderating role of PP in the relationship between technostress and academic staff performance. A PP is a dispositional tendency to take initiative, seek improvements and influence one's environment (Crant, 2000). Individuals high in proactivity tend to anticipate future problems, take preventive actions and persist in overcoming obstacles. Within the context of technology-mediated work environments, such individuals are better positioned to manage and adapt to technological demands, thus potentially mitigating the negative consequences of technostress (Parker, Wang & Liao, 2019). The empirical findings from the present study support this proposition. Multivariate analyses revealed a

significant positive relationship between PP and contextual performance under varying levels of techno-complexity, a core dimension of technostress.

The analysis demonstrated that a PP moderated the relationship between techno-complexity and CP. At low levels of techno-complexity, individuals with high proactiveness exhibited substantially higher levels of CP compared to those with lower proactiveness. For example, the predicted CP for individuals with low proactiveness (Proac = 43) was 30.65, while for those with very high proactiveness (Proac = 118) it reached 59.27. A similar trend was observed under moderate techno-complexity, although the baseline performance was slightly reduced. Under high techno-complexity conditions, the positive influence of proactiveness on CP remained statistically significant but diminished in magnitude. Individuals with low proactiveness exhibited a predicted CP of 1.47, statistically non-significant, whereas those with high proactiveness reached a CP of 30.10.

These findings indicate that a PP can buffer the adverse effects of technostress, particularly under conditions of low to moderate complexity. This is consistent with the results of prior studies. Proactive individuals appraise techno-stressors as opportunities rather than threats, which supports coping and sustained effectiveness (Zhao, Zhou, Liu & Kang, 2016). A proactive personality, defined as a tendency to take initiative to shape work conditions, enables successful adaptation in technology-intensive settings (Hung, Chen & Lin, 2015). Empirical evidence shows that proactive employees manage technostress more effectively and maintain performance under technological pressure (Wang, He, Liu & Zhou, 2022).

The Job Demands–Resources model explains this moderating role. Within this framework, technostress functions as a job demand, while proactive personality operates as a personal resource that supports effective coping and performance maintenance (Lin *et al.*, 2022). Findings in the present analysis align with the model, indicating sustained performance among proactive employees even when technology use becomes challenging.

A boundary condition also emerges. The moderating influence of proactive personality weakens in highly complex technological environments. When techno-complexity reaches extreme levels, proactive behaviour alone does not offset technostress.

External barriers, including poor system design, limited technical support and rigid institutional structures, constrain the benefits linked to proactivity (Srivastava, Chandra & Shirish, 2015).

#### **Hypothesis 7:**

- $H_{07}$ : PP does not moderate the relationship between technostress and academic staff performance.
- $H_{a7}$ : PP moderates the relationship between technostress and academic staff performance.

The null hypothesis ( $H_{07}$ ) was rejected, and the alternative hypothesis ( $H_{a7}$ ) was accepted. Thus, PP is confirmed as a significant moderating variable in the relationship between technostress and academic staff performance.

### **5.3 MANAGERIAL IMPLICATIONS AND RECOMMENDATIONS**

The finding that technostress significantly influences IWP among academic staff has several critical managerial implications, particularly in the African higher education context where resource constraints, technological disparities and socio-economic challenges often exacerbate the impact of technostress. Managers should take note of the following recommendations to formulate strategies to address this issue amicably.

Managers in the selected South African higher education institution should prioritise investments in reliable and user-friendly technological tools and systems. Outdated or overly complex technologies can heighten technostress, while modern, efficient and user-friendly systems can alleviate stressors such as techno-overload and techno-complexity. Academics in the selected university may lack sufficient training to manage rapidly evolving technologies. Managers should ensure regular professional development programmes focused on digital skills and adaptability to empower academic staff to navigate technological demands confidently, reducing technostress and enhancing work performance.

Institutional leaders, including deputy vice chancellors, academic deans, academic staff and relevant stakeholders, should adopt policies that expand digital literacy and

formalise coping mechanisms for technology use. These policies equip academic staff with the skills required to operate educational technologies and to manage associated strain. Higher education institutions should also adopt targeted policies to address techno overload among academic staff.

Managing techno overload is essential for institutional sustainability. The rapid adoption of digital tools in higher education necessitates clear guidelines to govern technology use by academic staff. Institutions should automate routine administrative tasks to release time for teaching, research and knowledge dissemination. Compulsory digital literacy training should form part of induction, with added support for staff with limited teaching experience. Academic deans and line managers should schedule regular training when introducing new systems to limit overload and protect performance. Awareness campaigns and mental well-being sessions can help staff identify and manage technostress. Open communication channels and peer support networks should allow staff to report challenges without barriers. Managers should also review the accessibility and responsiveness of IT support. Dedicated help desks and easily approached support teams can provide immediate assistance for technology-related issues.

Encouraging proactiveness helps to protect productivity when technology demands increase. Managers should recognise and reward proactive behaviour through clear appraisal criteria and aligned incentives. Regular, targeted training should build problem-solving, decision-making and critical thinking. Complex systems can lower the performance of staff who are less proactive. Institutions should simplify interfaces, provide clear guidelines and ensure robust IT support.

Managers and academic heads should involve academics in technology procurement. Complex systems that do not serve their intended purpose add to technology demands. Leaders promote proactive cultures by granting autonomy, giving constructive feedback and empowering staff to take initiative in solving work challenges.

Taken together, these actions enable higher education institutions in South Africa and similar settings to limit the adverse effects of technology adoption, support effective

technology use, strengthen the benefits of proactive behaviour and improve performance across varied technology demands.

#### **5.4 CONTRIBUTION OF THE STUDY**

This study advanced understanding of technostress in African higher education by examining its influence on individual work performance across task performance, contextual performance and counterproductive work behaviour. By focusing on academic staff, the study clarified how technology demands, technology self-efficacy and proactiveness shaped performance in higher education institutions. The analysis addressed constraints typical in African settings, including resource limits, digital literacy gaps and weak support structures, and offered practical steps to increase productivity while managing technostress.

The study extended a relatively underexplored body of work by tracing multidimensional effects of technostress on academic performance within African institutions. It showed that proactive behaviour and self-efficacy might help to counter techno-overload and techno-complexity in resource-constrained environments. The work provided a basis for future research by modelling links between technostress and individual work performance and by testing the moderating roles of proactiveness and technology self-efficacy.

Methodologically, the study demonstrated the value of structural equation modelling and multivariate multiple regression for estimating interactions among technostress, proactiveness and technology self-efficacy. The resulting model gives a practical template for future studies of similar complexity.

The findings have practical implications for institutions in less developed countries. Leaders can use these results to design training, support systems and policy settings that reduce technostress and improve academic performance. These strategies include:

- Encouraging proactive behaviours among academic staff
- Improving technological infrastructure
- Providing comprehensive training programs to enhance staff TSE

- Managing workloads to prevent techno-overload
- Promoting resilience in highly complex technological environments.

These strategies may help institutions reduce technostress, enhance staff productivity and improve professional well-being. By implementing these evidence-based interventions, higher education institutions can effectively navigate challenges in technology-intensive work environments.

## **5.5 LIMITATIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH**

The following section presents the limitations of this study and outlines future research directions to address each limitation.

Although the current study made a significant contribution to the body of knowledge through numerous notable findings and insights, like any other research it had several limitations that might be addressed in the future. Due to time constraints, the study collected data from a single higher education institution, which limits the generalisability of the findings to other institutions across the African continent. Higher education institutions vary widely in their use of technology for teaching and learning, which may influence the dynamics of technostress and its impact on academic performance. Future research could expand the scope to include multiple institutions, thereby enhancing the applicability of the results.

This study relied on quantitative methods to collect and analyse data. This approach provided robust statistical insights, yet it did not capture the whole experience of academic staff exposed to technostress. Future studies should include qualitative methods, for example, interviews or focus groups, to validate and enrich these results. Mixed methods research offers a more comprehensive view, since it combines numerical patterns with lived accounts.

The analysis examined two moderators—proactive personality and technology self-efficacy—to explain the reduction in technostress effects. These variables add value, yet other factors also shape this relationship. Organisational support, emotional intelligence and resilience are essential considerations. Future research should test additional moderators to build a richer view of technostress in higher education.

## 5.6 CONCLUSION

The primary objective of this study was to examine the influence of technostress on individual work performance among academic staff in a higher education institution, with a focus on developing a framework to assess this relationship.

The study found that technostress had a significant impact on work performance, with TSE and proactiveness playing moderating roles. Specifically, TSE was found to moderate the effects of techno-overload, while proactiveness enhanced CP across varying levels of techno-complexity. The empirical findings align with existing literature, confirming the critical role of personal resources in mitigating technostress. However, this study extended the literature by providing specific insights into the African higher education context, where the effects of technostress remain relatively underexplored.

Additionally, the study demonstrated the use of SEM and MMR in analysing complex, multi-dimensional relationships, providing a methodological contribution by proposing how SEM and MMR techniques could effectively evaluate moderating variables. From a practical perspective, the results indicate that higher education institutions in Africa must prioritise enhancing TSE and fostering proactiveness among academic staff to mitigate the negative impacts of technostress and improve performance outcomes. Furthermore, institutions should consider tailored strategies to address varying levels of techno-overload and complexity. This research provides a foundation for future studies and offers actionable recommendations for managing technostress in higher education.

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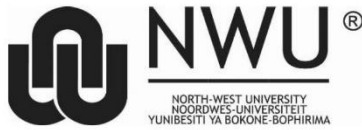
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## APPENDIX 1: NWU Ethical Clearance Letter



Private Bag X1290, Potchefstroom  
South Africa 2520

Tel: 018 299-1111/2222  
Fax: 018 299-4910  
Web: <http://www.nwu.ac.za>

**Senate Committee for Research Ethics**  
Tel: 018 299-484  
Feziwe.Mseleni@nwu.ac.za

31 March 2023

### ETHICS APPROVAL LETTER OF STUDY

Based on approval by the **Economic and Management Sciences Research Ethics Committee (EMS-REC)** on 31/03/2023, the Economic and Management Sciences Research Ethics Committee hereby **approves** your study as indicated below. This implies that the North-West University Senate Committee for Research Ethics (NWU-REC) grants its permission that, provided the special conditions specified below are met and pending any other authorisation that may be necessary, the study may be initiated, using the ethics number below.

|                                                                                                                                                                                                                                                                                                                                                                                                                                      |   |   |              |   |   |      |   |   |        |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |             |  |  |              |  |  |      |  |  |        |  |  |  |
|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---|---|--------------|---|---|------|---|---|--------|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|-------------|--|--|--------------|--|--|------|--|--|--------|--|--|--|
| <b>Study title: Developing a framework to assess the influence of technostress on academics' performance</b>                                                                                                                                                                                                                                                                                                                         |   |   |              |   |   |      |   |   |        |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |             |  |  |              |  |  |      |  |  |        |  |  |  |
| <b>Study Leader/Supervisor (Principal Investigator)/Researcher: Prof PA Botha- Economics</b>                                                                                                                                                                                                                                                                                                                                         |   |   |              |   |   |      |   |   |        |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |             |  |  |              |  |  |      |  |  |        |  |  |  |
| <b>Student: Maluleke AF(28494078)</b>                                                                                                                                                                                                                                                                                                                                                                                                |   |   |              |   |   |      |   |   |        |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |             |  |  |              |  |  |      |  |  |        |  |  |  |
| <table border="1"> <tr> <td>N</td><td>W</td><td>U</td><td>-</td><td>0</td><td>0</td><td>6</td><td>0</td><td>9</td><td>-</td><td>2</td><td>3</td><td>-</td><td>A</td><td>4</td> </tr> <tr> <td colspan="3">Institution</td> <td colspan="3">Study Number</td> <td colspan="3">Year</td> <td colspan="4">Status</td> </tr> </table> <p>Status: S = Submission; R = Re-Submission; P = Provisional Authorisation; A = Authorisation</p> |   |   |              |   |   |      |   |   |        |   |   |   | N | W | U | - | 0 | 0 | 6 | 0 | 9 | - | 2 | 3 | - | A | 4 | Institution |  |  | Study Number |  |  | Year |  |  | Status |  |  |  |
| N                                                                                                                                                                                                                                                                                                                                                                                                                                    | W | U | -            | 0 | 0 | 6    | 0 | 9 | -      | 2 | 3 | - | A | 4 |   |   |   |   |   |   |   |   |   |   |   |   |   |             |  |  |              |  |  |      |  |  |        |  |  |  |
| Institution                                                                                                                                                                                                                                                                                                                                                                                                                          |   |   | Study Number |   |   | Year |   |   | Status |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |             |  |  |              |  |  |      |  |  |        |  |  |  |
| <b>Application Type:</b><br><b>Commencement date: 1/4/2023</b><br><b>Expiry date: 1/5/2024</b>                                                                                                                                                                                                                                                                                                                                       |   |   |              |   |   |      |   |   |        |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |             |  |  |              |  |  |      |  |  |        |  |  |  |
| <b>Risk:</b> <span style="border: 1px solid black; padding: 2px;">Low</span>                                                                                                                                                                                                                                                                                                                                                         |   |   |              |   |   |      |   |   |        |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |             |  |  |              |  |  |      |  |  |        |  |  |  |
| <b>Approval of the study is initially provided for a year, after which continuation of the study is dependent on receipt and review of the annual (or as otherwise stipulated) monitoring report and the concomitant issuing of a letter of continuation.</b>                                                                                                                                                                        |   |   |              |   |   |      |   |   |        |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |             |  |  |              |  |  |      |  |  |        |  |  |  |

**Special in process conditions of the research for approval (if applicable):**

•

|                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                                |
|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| <p><b>General conditions:</b></p> <p><i>While this ethics approval is subject to all declarations, undertakings and agreements incorporated and signed in the application form, the following general terms and conditions will apply:</i></p> <ul style="list-style-type: none"> <li>• The study leader/supervisor (principle investigator)/researcher must report in the prescribed format to the EMS-REC: <ul style="list-style-type: none"> <li>– annually (or as otherwise requested) on the monitoring of the study, whereby a letter of continuation will be provided, and upon completion of the study; and</li> <li>– without any delay in case of any adverse event or incident (or any matter that interrupts sound ethical principles) during the course of the study.</li> </ul> </li> <li>• The approval applies strictly to the proposal as stipulated in the application form. Should any amendments to the proposal be deemed necessary during the course of the study, the study leader/researcher must apply for approval of these amendments at the EMS-REC, prior to implementation. Should there be any deviations from the study proposal without the necessary approval of such amendments, the ethics approval is immediately and automatically forfeited.</li> </ul> |
|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|

- *Annually a number of studies may be randomly selected for an external audit.*
- *The date of approval indicates the first date that the study may be started.*
- *In the interest of ethical responsibility, the NWU-SCRE and EMS-REC reserves the right to:*
  - *request access to any information or data at any time during the course or after completion of the study;*
  - *to ask further questions, seek additional information, require further modification or monitor the conduct of your research or the informed consent process;*
  - *withdraw or postpone approval if:*
    - *any unethical principles or practices of the study are revealed or suspected;*
    - *it becomes apparent that any relevant information was withheld from the EMS-REC or that information has been false or misrepresented;*
    - *submission of the annual (or otherwise stipulated) monitoring report, the required amendments, or reporting of adverse events or incidents was not done in a timely manner and accurately; and / or*
    - *new institutional rules, national legislation or international conventions deem it necessary.*

The EMS-REC would like to remain at your service as scientist and researcher, and wishes you well with your study. Please do not hesitate to contact the EMS-REC or the NWU-SCRE for any further enquiries or requests for assistance.

Yours sincerely,

**Mark  
Rathbone**

Digitally signed by Mark  
Rathbone  
DN: cn=Mark Rathbone,  
o=North-West University,  
ou=Business management,  
email=mark.rathbone@nwu.ac.za,  
c=ZA  
Date: 2023.04.12 13:43:13  
+02'00'

**Prof Mark Rathbone**  
**Chairperson: NWU Economic and Management Sciences Research Ethics Committee**

## APPENDIX 2: TUT Ethics Letter



### Research Ethics Committee

*The TUT Research Ethics Committee is a registered Institutional Review Board (IRB 00005968) with the US Office for Human Research Protections (IORG# 0004997). In addition, it has Federal Wide Assurance for the Protection of Human Subjects for International Institutions (FWA 00011501). In South Africa it is registered with the National Health Research Ethics Council (REC-160509-21).*

February 26, 2024

Mr AF Maluleke  
C/o Prof PA Botha  
Faculty of Economic and Management Sciences  
University of North West

REC Ref #: REC/2023/05/011  
Name: Maluleke AF  
Student #: 38494078, NWU

Dear Mr Maluleke,

**Decision: Final Approval**

**Name:** Maluleke AF

**Project title:** *Developing a framework to assess the influence of technostress on academics' individual performance in a selected higher education institution.*

**Qualification:** PhD in Economics and Management Sciences

**Supervisor:** Prof PA Botha

Thank you for submitting the revised project documents for review by the Research Ethics Committee (REC), Tshwane University of Technology (TUT). In reviewing the documents, the comments and notes below are tabled for your consideration, attention and/or notification:

- **Permission Letters**

- **TUT, E-mail Distribution.** The permission letter from Dr E Mabote, Acting Director of Institutional Effectiveness and Transformation (Letter dated February 21, 2024) is in order.



*We empower people*

The acting chairperson of the Tshwane University of Technology Research Ethics Committee reviewed the revised project documents on February 26, 2024. **Final Approval** has been granted to the project.

The proposed research project may now continue with the proviso that:

- 1) The researcher/s will conduct the study according to the procedures and methods indicated in the **approved proposal**, particularly in terms of any undertakings and/or assurances made regarding the confidentiality of the collected data.
- 2) The proposal will be submitted to the Committee for prospective ethical clearance if there are any substantial **deviations** and/or changes from the approved proposal.
- 3) The researcher/s will act within the parameters of any applicable **national legislation, professional codes of conduct**, institutional guidelines and scientific standards relevant to the specific field of study. Strict adherence to the following South African legislation, where applicable, is especially important: Protection of Personal Information Act (Act 4 of 2013), Children's Act (Act 38 of 2005) and the National Health Act (Act 61 of 2003).
- 4) The researcher will inform the REC as soon as possible of any **adverse events** involving research participants that may have occurred during the course of the study. It includes the actions and/or processes that were implemented to mitigate and/or prevent any further injuries and/or adverse outcomes.
- 5) The researcher will inform the REC of any **new or unexpected ethical issues** that may have emerged during the course of the study, as well as how these ethical issues were addressed. The researcher must consult with the REC for advice and/or guidance in any such event.
- 6) The current ethics approval expiry date for this project is **February 25, 2026**. No research activities may continue after the ethics approval expiry date. An application for the extension of ethics approval must be submitted for projects that need to continue beyond the expiry date.
- 7) It is a strict requirement for the researcher to submit a progress report before **February 25, 2025**.

Note:

The reference number [top right corner of this communiqué] should be clearly indicated on all forms of communication [e.g. Webmail, E-mail messages, letters] with the intended research participants.

Yours sincerely,



Prof JN Agumba  
Deputy Chairperson: Research Ethics Committee  
[TUTRef #2023=05=011=MalulekeAF]



**We empower people**

Tel. 0861 102 422, Tel. (012) 382-5911, Fax (012) 382-5114, www.tut.ac.za • The Registrar, Private Bag X680, Pretoria 0001

**APPENDIX 3: TUT Gatekeepers Letter**

**Tshwane University  
of Technology**

Institutional Effectiveness and Technology

---

23 February 2024

Mr AF Maluleke  
C/o Prof PA Botha  
Faculty of Economic and Management Sciences  
University of North-West

Dear Mr Maluleke

**GATEKEEPER PERMISSION LETTER**

Your request for gatekeeper's permission and the Tshwane University of Technology (TUT) Research Ethics Committee (REC) provisional approval letter dated 1 February 2024 for the research project "Developing a framework to assess the influence of technostress on academics' individual performance in a selected higher education institution" are duly acknowledged.

I am pleased to inform you that your request has been reviewed and permission is granted to access the contact details of the targeted TUT stakeholders from the Management Information System (MIS). Please note that permission is granted on condition that you fulfill the conditions as stipulated in the TUT REC provisional approval letter.

Wishing you all the best with your studies.

Yours sincerely,

A handwritten signature in black ink, appearing to read 'Mabote'.

Dr NE Mabote  
**ACTING EXECUTIVE DIRECTOR: IE&T**



---

*We empower people*

Tel. (012) 382-4401, [mabotene@tut.ac.za](mailto:mabotene@tut.ac.za), [www.tut.ac.za](http://www.tut.ac.za), Private Bag X680, Pretoria 0001

## APPENDIX 4: Questionnaire

### LETTER OF INVITATION TO PARTICIPATE IN A PHD STUDY

Dear academic staff member

I am writing to invite you to participate in my PhD study entitled ***Developing a Framework to Assess the Influence of Technostress on Academic Staff Performance***. This study aims to develop a framework to assess the influence of technostress (independent variable) on academic staff's performance (dependent variable) and the moderating role of technology self-efficacy and proactive personality in a selected higher education institution. The secondary objectives are to establish the reliability and validity of the measuring instruments in the South African Higher Education context, determine if there is a relationship between technostress and individual work performance, and assess the moderating role of technology self-efficacy and proactive personality in the relationship between technostress and academic staff's 'performance. The research questions include: are the measuring instruments reliable and valid in the South African Higher Education context?; is there a relationship between technostress and individual work performance?; and do technology self-efficacy and proactive personality act as moderators in the relationship between technostress and academic staff performance?

You have been identified as a potential participant in this study because of your expertise and experience as an academic staff member of the Tshwane University of Technology. Your participation in this study would be invaluable to achieving the goals of the research and advancing our understanding of the impact of technostress on individual work performance and the moderator roles of technology self-efficacy and proactive personality.

Participation in this study involves completing an electronic questionnaire at the attached hyperlink. The estimated time commitment for participation is between 30 – 45 minutes.

Your participation in this study is entirely voluntary, and you may withdraw at any time without consequence. Your responses will be kept confidential and anonymous to the extent possible by assigning a pseudonym to each participant.

If you agree to participate, please respond to this letter with your consent and a convenient time and method for us to arrange a meeting. If you have any questions or concerns, please do not hesitate to contact me.

Thank you for considering this invitation to participate in my study.

Yours sincerely

AF Maluleke

Researcher

0725260786

ferozmaluleke@gmail.com

## **SECTION 1: DEMOGRAPHIC INFORMATION**

### **1. Please indicate your gender.**

|        |   |
|--------|---|
| Male   | 1 |
| Female | 2 |
| Other  | 3 |

### **2. Indicate your age group.**

|              |   |
|--------------|---|
| 20 – 29      | 1 |
| 30 – 39      | 2 |
| 40 – 49      | 3 |
| 50 – 59      | 4 |
| 60 and older | 5 |

### **3. Indicate your job level.**

|                     |   |
|---------------------|---|
| Junior lecturer     | 1 |
| Lecturer            | 2 |
| Senior lecturer     | 3 |
| Associate-professor | 4 |
| Full professor      | 5 |
| Other               | 6 |

### **4. Indicate your campus.**

|                               |   |
|-------------------------------|---|
| Arcadia Campus                | 1 |
| Arts Campus,                  | 2 |
| Pretoria Campus,              | 3 |
| Ga-Rankuwa Campus             | 4 |
| North Campus in<br>Soshanguve | 5 |
| South Campus in<br>Soshanguve | 6 |
| eMalahleni Campus             | 7 |
| Mbombela Campus               | 8 |
| Polokwane Campus              | 9 |

### **5. Please indicate your faculty**

|                                          |   |
|------------------------------------------|---|
| Arts and Design                          | 1 |
| Economics and Finance                    | 2 |
| Engineering and the Built Environment    | 3 |
| Humanities                               | 4 |
| Information and Communication Technology | 5 |
| Management Sciences                      | 6 |
| Science                                  | 7 |

## SECTION 2: TECHNOSTRESS QUESTIONNAIRE

In the following statements, the term "" this technology"" refers to the day-to-day computer applications you use in your job, such as e-mails, office automation systems, database systems, and any other job-related information technologies. Rate your level of agreement with each statement on a 5-point Likert scale, where 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree.

### Techno-Overload

- TS1 I am forced by this technology to work much faster
- TS2 I am forced by this technology to do more work than I can handle
- TS3 I am forced by this technology to work with very tight time schedules.
- TS4 I am forced to change my work habits to adapt to new technologies.
- TS5 I have a higher workload because of increased technology complexity.
- TS6 I spend less time with my family due to this technology.

### Techno-Invasion

- TS7 I have to be in touch with my work even during my vacation due to this technology.
- TS8 I have to sacrifice my vacation and weekend time to keep current on new technologies.
- TS9 I feel my personal life is being invaded by this technology.

### Techno-Complexity

- TS10 I do not know enough about this technology to handle my job satisfactorily.
- TS11 I need a long time to understand and use new technologies.
- TS12 I do not have enough time to study and upgrade my technology skills.
- TS13 I find new employees to this organisation know more about computer technology than I do.
- TS14 I often find it too complex for me to understand and use new technologies.

### Techno-Insecurity

- TS15 I feel constant threat to my job security due to new technologies.
- TS16 I have to constantly update my technology skills to avoid being replaced.
- TS17 I am threatened by co-workers with newer technology skills.
- TS18 I do not share my knowledge with my coworkers for fear of being replaced.
- TS19 I feel there is less sharing of knowledge among co-workers for fear of being replaced.

### Techno-Uncertainty

- TS20      There are always new developments in the technologies we use in our organisation.
- TS21      There are constant changes in computer software in our organisation.
- TS22      There are constant changes in computer hardware in our organisation.
- TS23      There are frequent upgrades in computer networks in our organisation.

**Source:** Chen L (2015) *Validating the Technostress Instrument using a Sample of Chinese Knowledge Workers*

### SECTION 3: INDIVIDUAL WORK PERFORMANCE QUESTIONNAIRE

Please complete the Individual Work Performance Questionnaire, reflect on your work-related behaviours and actions relevant to your university's goals over the past three months, and rate your agreement with the statements provided using the specified scale. The Likert scale for Task Performance and Contextual Performance ranges from 1 (Never) to 5 (Always), indicating how often the respondent engages in the specific work behaviour. For Counterproductive Work Behavior, the scale ranges from 1 (Never) to 5 (Always), indicating the frequency of engaging in behaviour detrimental to organisational goals.

| Items                                               |                                                                                           |
|-----------------------------------------------------|-------------------------------------------------------------------------------------------|
| <b>Task performance (TP) scale</b>                  |                                                                                           |
| In the past 3 months...                             |                                                                                           |
| TP1                                                 | I managed to plan my work so that it was done on time.                                    |
| TP2                                                 | My planning was optimal.                                                                  |
| TP3                                                 | I kept in mind the results that I had to achieve in my work.                              |
| TP4                                                 | I was able to separate main issues from side issues at work.                              |
| TP5                                                 | I was able to perform my work well with minimal time and effort                           |
|                                                     |                                                                                           |
| <b>Contextual performance (CP) scale</b>            |                                                                                           |
| In the past 3 months...                             |                                                                                           |
| CP1                                                 | I took on extra responsibilities.                                                         |
| CP2                                                 | I started new tasks myself, when my old ones were finished.                               |
| CP3                                                 | I took on challenging work tasks when available.                                          |
| CP4                                                 | I worked at keeping my job knowledge up-to-date.                                          |
| CP5                                                 | I worked at keeping my job skills up-to-date.                                             |
| CP6                                                 | I came up with creative solutions to new problems.                                        |
| CP7                                                 | I kept looking for new challenges in my job.                                              |
| CP8                                                 | I actively participated in work meetings.                                                 |
|                                                     |                                                                                           |
| <b>Counterproductive work behaviour (CWB) scale</b> |                                                                                           |
| In the past 3 months                                |                                                                                           |
| CWB1                                                | I complained about unimportant matters at work.                                           |
| CWB2                                                | I made problems greater than they were at work                                            |
| CWB3                                                | I focused on the negative aspects of a work situation instead of on the positive aspects. |
| CWB4                                                | I spoke with colleagues about the negative aspects of my work.                            |
| CWB5                                                | I spoke with people from outside the organization about the negative aspects of my work.  |

**Source:** Koopmans, L., Bernaards, C.M., Hildebrandt, V.H., de Vet, H.C. & van der Beek, A.J., 2014. Construct validity of the individual work performance questionnaire. *Journal of occupational and environmental medicine*, 56(3), pp.331-337

## SECTION 4: TECHNOLOGY SELF-EFFICACY INSTRUMENT

Below are several statements regarding one's general beliefs and attitudes towards your technology self-efficacy. Please rate yourself on a 6-point Likert scale ranging from 1 (Not at All) to 6 (A Great Deal)

| Statements |                                                                                                                                                  | Not at all | Very little | A little | Somewhat | Quite a bit | A great deal |
|------------|--------------------------------------------------------------------------------------------------------------------------------------------------|------------|-------------|----------|----------|-------------|--------------|
| 1          | How competent do you perceive yourself in selecting and using various media to support teaching and learning?                                    | 1          | 2           | 3        | 4        | 5           | 6            |
| 2          | How well prepared are you to evaluate software to support teaching and learning?                                                                 | 1          | 2           | 3        | 4        | 5           | 6            |
| 3          | To what extent can you integrate technology across the curriculum?                                                                               | 1          | 2           | 3        | 4        | 5           | 6            |
| 4          | How capable are you of determining why, when and how to use technology in education?                                                             | 1          | 2           | 3        | 4        | 5           | 6            |
| 5          | To what extent do you feel prepared to select and utilise assistive technologies?                                                                | 1          | 2           | 3        | 4        | 5           | 6            |
| 6          | To what extent did you incorporate technology to enhance teaching and learning in the lessons you taught in your field experience this semester? | 1          | 2           | 3        | 4        | 5           | 6            |

Kent, A. M., & Giles, R. M. (2017). Preservice teachers' technology self-efficacy. *SRATE Journal*, 26(1), 9-20.

## SECTION 5: THE PROACTIVE PERSONALITY SCALE

Please complete the questionnaire on proactive behaviour and reflect on your actions and tendencies to effect environmental change. Use the provided Likert scale, typically "Strongly Disagree" to "Strongly Agree," to rate each statement based on how well it describes your experiences and beliefs in influencing your surroundings. Responses are indicated on a 7-point Likert scale, where 1 signifies "Strongly Disagree" and 7 signifies "Strongly Agree".

| Item                                                                               | Likert Scale (1-7)                         |
|------------------------------------------------------------------------------------|--------------------------------------------|
| 1. I am constantly on the lookout for new ways to improve my life.                 | Strongly Disagree (1) - Strongly Agree (7) |
| 2. I feel driven to make a difference in my community and maybe the world.         | Strongly Disagree (1) - Strongly Agree (7) |
| 3. I tend to let others take the initiative to start new projects. (Reverse coded) | Strongly Disagree (1) - Strongly Agree (7) |
| 4. Wherever I have been, I have been a powerful force for constructive change.     | Strongly Disagree (1) - Strongly Agree (7) |

|                                                                                 |                                               |
|---------------------------------------------------------------------------------|-----------------------------------------------|
| 5. I enjoy facing and overcoming obstacles to my ideas.                         | Strongly Disagree (1) -<br>Strongly Agree (7) |
| 6. Nothing is more exciting than seeing my ideas turn into reality.             | Strongly Disagree (1) -<br>Strongly Agree (7) |
| 7. If I see something I don't like, I fix it.                                   | Strongly Disagree (1) -<br>Strongly Agree (7) |
| 8. No matter what the odds, if I believe in something, I will make it happen.   | Strongly Disagree (1) -<br>Strongly Agree (7) |
| 9. I love being a champion for my ideas, even against others' opposition.       | Strongly Disagree (1) -<br>Strongly Agree (7) |
| 10. I excel at identifying opportunities.                                       | Strongly Disagree (1) -<br>Strongly Agree (7) |
| 11. I am always looking for better ways to do things.                           | Strongly Disagree (1) -<br>Strongly Agree (7) |
| 12. If I believe in an idea, no obstacle will prevent me from making it happen. | Strongly Disagree (1) -<br>Strongly Agree (7) |
| 13. I love to challenge the status quo.                                         | Strongly Disagree (1) -<br>Strongly Agree (7) |
| 14. When I have a problem, I tackle it head-on.                                 | Strongly Disagree (1) -<br>Strongly Agree (7) |
| 15. I am great at turning problems into opportunities.                          | Strongly Disagree (1) -<br>Strongly Agree (7) |
| 16. I can spot a good opportunity long before others can.                       | Strongly Disagree (1) -<br>Strongly Agree (7) |
| 17. If I see someone in trouble, I help out in any way I can.                   | Strongly Disagree (1) -<br>Strongly Agree (7) |

**Source:** Gentry, J.E., Baker, C., Thomas, B.D., Whitfield, C. & Garcia, L., 2014. Transforming Technology Integration: An Instrument to Measure Educator's Self-Efficacy for Modeling 21st-Century Skills. *National Teacher Education Journal*, 7(3).