



## DOCTORATE IN BUSINESS ADMINISTRATION

**Masialeti Masialeti**

### **An empirical study of short interval control tasks and mobile technology fit in an underground mine**

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**Thesis Supervisor:** Prof. Jean-Fabrice Lebraty

iaelyon School of Management, Université Jean Moulin Lyon 3 (France)

**Thesis Jury:** Prof. Michel Kalika

iaelyon School of Management, Université Jean Moulin Lyon 3 (France), **Jury President**

**Prof. Jessie Pallud**

EM Strasbourg Business School, **Examiner**

**Prof. Christophe Fournier**

IAE ontpellier , **Examiner**

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## ABSTRACT

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Digital transformation has become a key strategic objective for many mining companies. Mobile technology has recently become a platform of choice for the digital implementation of short interval control (SIC) tasks. This study empirically investigated the SIC tasks of planning, execution, and control via mobile technology in the mining industry at Turquoise Ridge Underground (TRU) gold mine in Nevada, the USA. Specifically, the proposed new task-technology fit (TTF) theory by Howard and Rose (2019) was used as a framework of analysis to assess the fit between SIC tasks and mobile technologies to drive miners' performance at TRU. A web survey was carried out among 200 sampled underground miners. The resulting research model was analysed using the partial least squares-structural equation modeling (PLS-SEM) approach. The research findings reveal that the interactive effect of SIC task characteristics and mobile technology characteristics mediated by TTF has no statistically significant effect on underground miner reactions, utilisation of mobile technology, and performance outcomes of miners. However, the direct effect of mobile technology characteristics on TTF, TTM – "Too Much" and TTM – "Too Little" is statistically significant. These results revealed that TTF significantly predicts underground miner reaction, utilisation, and performance outcomes. The study suggests that Task-Technology Fit (TTF) results in better prediction, thus allowing for better decision making around improving the SIC process, which results in better performance of underground miners. However, Task-Technology Misfit (TTM) is unpredictable and therefore makes it challenging to make decisions on improvement, thus negatively impacting performance. In addition, the results suggest that we can assess the differences between TTF and TTM in terms of the capability of performance prediction. Theoretical and managerial implications are suggested because of the findings of the study.

**Keywords:** Mining, Mobile Technology, Short Interval Control, Task-Technology Fit, Task-Technology Misfit, Turquoise Ridge Underground

## RÉSUMÉ

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La transformation numérique est devenue un objectif stratégique clé pour de nombreuses sociétés minières. La technologie mobile est récemment devenue une plate-forme de choix pour la mise en œuvre numérique de tâches de contrôle à intervalle court (short interval control - SIC). Cette étude a examiné de manière empirique les tâches SIC de planification, d'exécution et de contrôle via la technologie mobile dans l'industrie minière à la mine d'Or de Turquoise Ridge Underground (TRU) dans le Nevada, aux États-Unis. Plus précisément, la nouvelle théorie de l'adéquation tâche-technologie (task-technology fit - TTF) proposée par Howard & Rose (2019) a été utilisée comme cadre d'analyse pour évaluer l'adéquation entre les tâches SIC et les technologies mobiles pour améliorer les performances des mineurs à TRU. Une enquête en ligne a été réalisée auprès de 200 mineurs de fond échantillonnés. Le modèle de recherche résultant a été analysé à l'aide de l'approche de modélisation par l'équation structurelle des moindres carrés partiels (PLS-SEM). Les résultats de la recherche révèlent que l'effet interactif des caractéristiques des tâches SIC et des caractéristiques de la technologie mobile médiée par TTF n'a pas d'effet statistiquement significatif sur les réactions des mineurs souterrains, l'utilisation de la technologie mobile et les résultats de performance des mineurs. Cependant, l'effet direct des caractéristiques de la technologie mobile sur TTF, TTM - "Too Much" et TTM - "Too Little" est statistiquement significatif. Ces résultats ont révélé que TTF prédit de manière significative la réaction, l'utilisation et les performances des mineurs souterrain. L'étude suggère que l'ajustement entraîne une meilleure prédiction, permettant ainsi une meilleure prise de décision concernant l'amélioration du processus SIC, ce qui entraîne une meilleure performance des mineurs souterrain. Cependant, l'inadéquation est imprévisible et rend donc difficile la prise de décisions sur l'amélioration, ce qui a un impact négatif sur les performances., les résultats suggèrent que nous pouvons évaluer les différences entre l'ajustement et l'inadéquation en termes de capacité de prédiction de la performance. Des implications théoriques et managériales sont suggérées en raison des résultats de l'étude.

**Mots-clés** : exploitation minière, technologie mobile, contrôle à intervalle court, ajustement tâche-technologie, Inadéquation tâche-technologie, mine souterraine de Turquoise Ridge

## DEDICATION

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This thesis is dedicated to my wife, Sally Mwewa Kuyeli, and our beloved children, Joseph Kashompa Masialeti and Alisa Kashompa Masialeti. They endured, sacrificed, and supported me during the difficult times of balancing work, family, and school. I also dedicate this work to my wonderful and hardworking parents, Charles Kashompa Masialeti and Josephine Chishala Muyeba, who genuinely took good care of my education from when I was young.

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## LIST OF ACRONYMS AND ABBREVIATIONS

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3D	three-dimensional
AVE	average variance extracted
BGC	Barrick Gold Corporation
CSV	comma separated values
DBA	doctor of business administration
DT	digital transformation
ESG	environmental, social and governance
GDP	gross domestic product
GMG	Global Mining Guidelines
HTMT	heterotrait-monotrait ratio
IoT	Internet of Things
IPMA	importance-performance map analysis
IR 4.0	Industrial Revolution 4.0
IS	information systems
MNIS	mobile nursing information system
NFI	normed fit index
NGM	Nevada Gold Mines
NMA	National Mining Association
PDCA	plan-do-check-act
PLS-SEM	part least squares structural equation modelling
PwC	PricewaterhouseCoopers
SEM	structural equation modelling
SIC	short interval control
SRMR	standardised root mean squared residual
TAM	technology acceptance model
TPC	technology-to-performance chain
TRU	Turquoise Ridge Underground
TTF	task-technology fit
TTM	task-technology misfit
USA	United States of America
UTAUT	unified theory of acceptance and use of technology
VIF	variance inflation factor
WEF	World Economic Forum

## CHAPTER 1: INTRODUCTION

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### 1.1 Introducing the chapter

This chapter presents the drivers for digital transformation (DT) identified in the mining industry in general and Turquoise Ridge Underground (TRU) in particular and discusses the digitisation of the short interval control (SIC) process that the TRU Division had implemented as an emerging mining DT initiative. The task-technology fit (TTF) theory is introduced as a key aspect of DT in SIC. Further, the chapter presents the problem statement, identifying gaps in current studies of SIC and TTF, the research questions and the objectives. The research design which was used to study the gaps identified while addressing the research questions raised is also presented in this chapter.

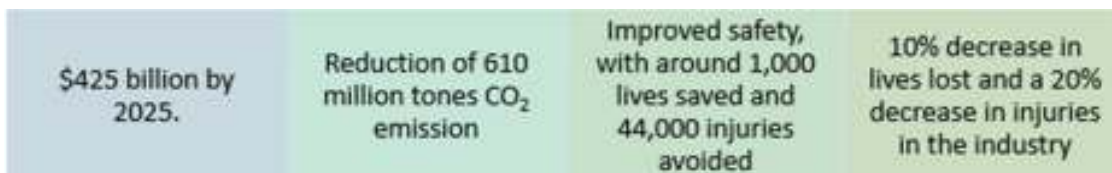
### 1.2 Background of the study

The mining industry has existed globally for a long time. It contributes to the gross domestic product (GDP) in many countries (Ericsson & Löf, 2019; Mining Association of Canada, 2019). For example, in the USA, the supply chain of the mining industry generated 3.02 trillion USD for the economy of 2018, representing more than 14% of the GDP while providing more than 1.1 million jobs (National Mining Association [NMA], 2019).

In general, the progress of the mining industry depends primarily on the metal prices, licence to operate, environmental, social, and governance (ESG) criteria, ore deposit, production process, cost-saving initiatives, and management approach (Rahm, 2013). For example, Vale, a Brazilian mining giant, recorded a financial impact of \$4.95 billion from the Brumadinho dam disaster (Lewis, 2019). Other issues related to social licences to operate, such as strikes and a lack of societal support for commercial enterprises, have also negatively impacted the mining industry. Besides, many shareholders are increasingly concerned about safety issues in the mining industry, especially when the ore bodies are getting deeper and a higher capital investment is required to minimise the risk of accessing the ore (World Economic Forum [WEF], 2020). These factors have led many experts to re-strategise the mode of operation for mining with the goal of making it rewarding, sustainable, and socially admissible (WEF, 2020).

In this respect, DT has become a key strategic objective for many mining enterprisers (Maquinaria Magazine, 2012; Moore, 2019; Nott, 2018; Zhou, 2019) to turn around their business models by implementing computer-based technologies, such as autonomous systems, workable hardware, digitally-empowered staff, concatenated businesses, platforms and ecosystems, and next-generation analytical technique for decision-making (WEF, 2020). Applications of artificial intelligence and automation are particularly relevant to the mining industry in minimising the risk of the workforce, reducing the impact on the environment and ecosystem while increasing the return (Schmelzer, 2020). The first two decades of the 21st century witnessed many industrial successes in applying computer-based technologies, thus motivating the mining industry to consider DT as the primary choice for revamping their operations. For example, in the transportation sector, the introduction of Uber revolutionised the whole industry. In the hospitality industry, Airbnb has become the main competitor for traditional players.

Recently, the WEF (2020) published white papers on the DT for mineral extractions with discrete case studies. Figure 1.1 shows its impact assessment of DT on the mining industry.



**Figure 1.1: The impact of digital transformation on the mining industry estimated by the WEF.**

Source: WEF, 2020.

Many chief executives of the mining industry supported DT programmes. John L. Thornton, the Executive Chairman of Barrick Gold Corporation, commented as follows:

*“Harnessing the potential of digital technology will unlock value across our business. In so doing, we will make ourselves into a leading twenty-first-century company — enhancing safety, productivity, and efficiency at our mines, and improving decision-making and performance across every area of our business” (CISCO, 2017).*

Most mining companies are either planning to implement or have already implemented various DT initiatives. For example, Barrick Gold Corporation (BGC), the world’s second-largest

producer of gold by ounces, implemented an automation revamping initiative at Kibali Gold Mine in the Democratic Republic of Congo. Its CEO, Mark Bristow, said the installation of the digital Newtrax system "would enhance the effectiveness in managing staff safety, predictive maintenance, and fleet-tracking with real-time data" (Barrick, 2019). Kibali Gold Mine would also assess the efficiency of this high-tech system by comparing manned and remote-controlled operations in the same area (Barrick, 2019).

BHP Mitsubishi Alliance (BMA) Company implemented a robotic haulage system at its Goonyella Riverside coal mine in Queensland, Australia, to decrease the truck time with a more predictable cycle duration, thereby reducing the workforce's exposure to hazards. Another mine at the forefront of implementing DT technologies is TRU at Nevada Gold Mines (NGM) LLC that operates both underground and open-pit mining in northern Nevada, the USA. NGM LLC is jointly owned by BGC and Newmont Corporation (Newmont) but operated by BGC, the main shareholder.

### **1.3 Problem statement**

Among the many digital transformation initiatives implemented by many mining companies is digital SIC. BGC implemented digital SIC at TRU (Barrick, 2019). The GMG Group (2019) defines SIC as a structured process which involved examining data at short intervals all through the shift to correct real-time deviations. As a result, SIC serves as a formal framework for managing shift tasks and evaluating actual performance against anticipated output (Savit et al., 2018). This procedure enables supervisors to make mid-shift adjustments to increase overall production efficacy and efficiency (Savit et al., 2018). Because underground mining changes might last up to 12 hours, review intervals can range from once every six hours to once every hour or less (GMG Group, 2019). Therefore, SIC improves shift-level planning, optimises cycle times, personnel and utilisation, and production control via an effective loop known as plan-do-check-act (PDCA) for mining processes (Global Mining Guidelines [GMG] Group, 2019; Savit et al., 2018). Howes and Forrest (2012) reviewed the Chelopech Mining EAD (CMEAD) SIC case study and it was found that SIC was being utilised in an underground mine to improve shift time and asset utilisation. The GMG Group (2019) identified the advantages of SIC. These include changes to real-time operations, which depend on real-time conditions to achieve short-term planning and shift goals, as well as lowering costs and increasing productivity in the mining industry. The other advantages are improving environmental performance, mine safety, and overall equipment efficacy, as well as streamlining processes

and easing supervisory burdens. By enabling the PDCA loop, SIC seeks a continuous enhancement cycle for minimal waste and higher production in the mining segment, according to the GMG Group (2019).

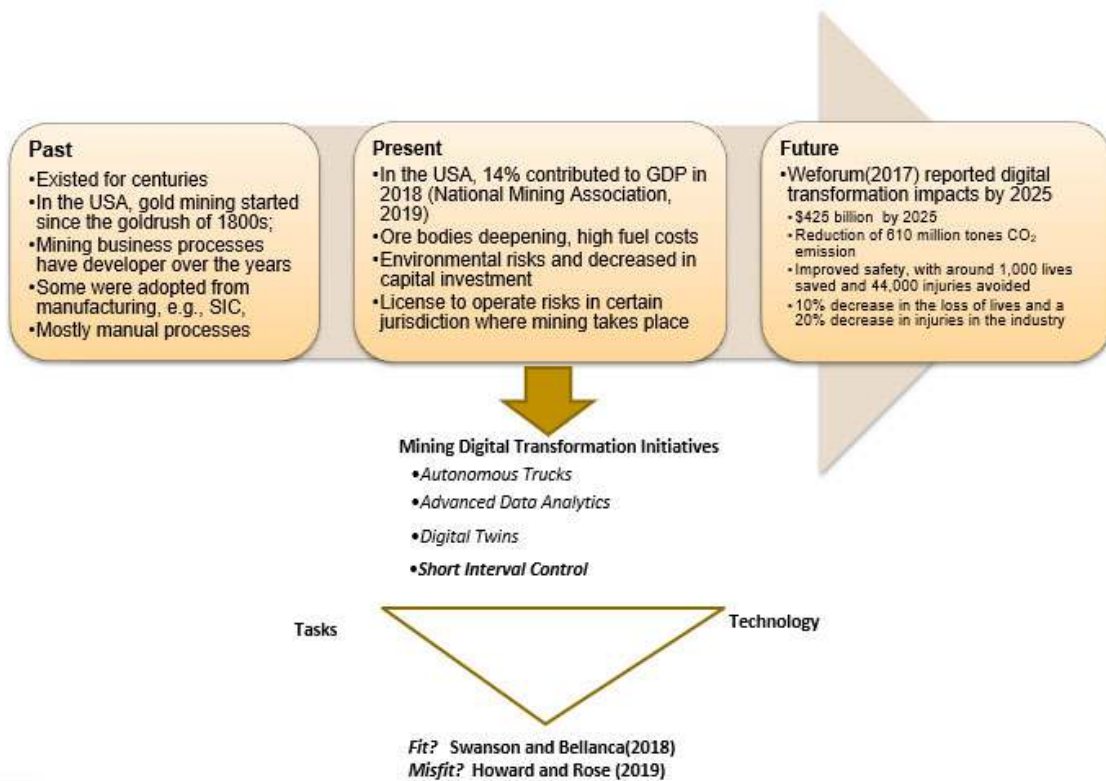
Due to the unpredictability of working conditions in the underground mine, the GMG Group (2019) asserted that SIC is new to the mining environment and generally has been done manually. With the increase of newer technologies, which are part of Industry 4.0, the SIC process has been undergoing changes. The installation of cutting-edge technology and communication infrastructure in underground settings has created a plethora of chances to use SIC to manage shifts (GMG Group, 2019). For example, more and more mobile technologies are being used as part of the SIC implementation. The change from recording data on paper to mobile technologies such as smartphones and tablets, minimises manual mistakes, substantially enhancing the command centre's rapid assessment of operations (Savit et al., 2018). Further, digitally managed critical decisions about compliance with environmental impact regulations and health and safety standards in the mining industry require ample accurate information. This digital data collected via mobile technology provides the management team with operational intelligence for data-driven decision making.

Although there are many benefits reported regarding the use of mobile technology enabled SIC, there is lack of empirical evidence to explain SIC tasks and mobile technologies characteristics fit and misfit and how this would enhance underground mine workers' performance. Therefore, this study sought to address the problem by using the new TTF/M model proposed by Howard and Rose (2019). This model was developed from the work of Goodhue and Thompson (1995) who asserts that there should be a good fit or alignment between task and information systems characteristics to augment the increased usage of technology and individual performance. Goodhue and Thompson (1995) authors brought insight from two research streams, i.e., the operator's attitude as a predictor of usage and TTF as a predictor of performance. Based on empirical assessments, they argued that information systems would enhance performance only when there is a good fit between practicality and operators' needs for the work.

The TTF model has been used in various contexts and even combined with other information frameworks such as the technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT), etc. Since the performance of TTF is applicable at both individual (Goodhue & Thompson, 1995) and group-level (Zigurs & Buckland, 1998), it is generally perceived that the usage of the TTF model will be continued (Furieux, 2011).

Nevertheless, Howard and Rose (2019) argued that the TTF model needed refinement, particularly in its conceptualisation and operationalisation. They believe that the model has emphasised the fit, neglecting the 'misfit' and over-stressing the direct effects. They argued that although TTF and task-technology misfit (TTM) are different, they can be complementary. Based on empirical studies, Howard and Rose (2019) proposed a broader TTF theoretical framework that encompasses TTM.

Overall, although the TTF has been well evaluated in various contexts, such as education (McGill & Hobbs, 2007; D'Ambra, Wilson & Akter, 2012; Robles-Flores & Roussinov, 2012), engineering (Dare-Abel, 2014), insurance (Kishokumar & Thiyagarajan, 2015), finance (Musyaffi & Muna, 2020), manufacturing (Mikalef, Torvatn & Arica, 2019), and coal mining (Swanson & Bellanca, 2018) etc., little is known about the effectiveness of using SIC via mobile technology in the underground gold mining, i.e. whether it is a good fit or misfit. Thus, there is a need for conducting such assessments. Figure 1.2 shows the conceptualisation of the past, present, future, and gaps in DT in the mining industry. The future conceptualisation represents the impact assesement of DT on the mining industry (WEF, 2020).



**Figure 1.2: Past, present, future, and gaps in digital transformation in the mining industry**

Source: WEF, 2020.

#### **1.4 Purpose of the study**

This study intended to quantitatively assess and improve the fit between SIC tasks and mobile technologies in driving the individual performance of miners at the TRU gold mine Division.

#### **1.5 Research aims, questions, and objectives**

It is in this section where the focus of the study is narrowed by specifying the research questions that addressed the problem statement.

The **research aimed** to contribute to the body of knowledge of task technology fit by assessing the fit and misfit implications of short interval control tasks and mobile technologies used by miners within the context of an underground gold mine.

The **research question** for the present study was as follows:

***Primary question:*** *What are the implications of short interval control tasks fit and misfit with mobile technology applications used by operational level miners in an underground gold mine?*

This research also aimed to assess the competence of SIC tasks and mobile technologies used by underground gold miners. Specifically, the following were the objectives of this research:

- To review the literature and discuss the original and refined or extended theory of TTF
- To deliberate the application of TTF in other industries
- To describe the SIC tasks using the Deming Plan-Do-Check- Act (PDCA) model
- To examine the characteristics of mobile technology
- To deliberate the case study of TRU
- To propose new constructs and variables for the TTF model for SIC tasks.
- To provide theoretical contribution and managerial recommendations.

#### **1.6 Relevance and significance of the study**

This study contributes to improving the implementation and management of the digital SIC in the mining industry via analyses of data and variables specific to underground gold mining, using the framework of TTF theory. Specifically, this study has developed a refined

questionnaire as a fit assessment tool that practitioners and academicians can use to evaluate the SIC systems. Finally, this study offers managerial recommendations for improving the implementation and management of digital SIC mobile systems, which can be crucial for the mining industry's DT systems.

### **1.7 Research methodology and design**

This study used a positivist approach and quantitative analyses as the primary research methodology. Data were collected via a survey questionnaire specifically directed to the sample of staff of the TRU gold mine as a case study. The target population composed of 500 employees, and a purposive sample of 200 was randomly chosen for the distribution of the questionnaire.

Descriptive statistics and the partial least squares - structural equation model (PLS-SEM) was used to analyse the collected data. Specifically, descriptive statistics were analysed with the software Statistical Package for the Social Sciences (version 21, IBM) and the structural equation modelling with Smart PLS 3.3.3 (Ringle, Wende, & Becker, 2015). Chapter 4 furnishes the details of the research design.

### **1.8 Assumptions and delimitations**

The fundamental assumption of this study was that investigation took place at a mine that had implemented DT, specifically the digital SIC tasks using mobile technology.

This study was conducted at TRU of NGM LL, Nevada, USA, from April 2019 to May 2021. This mine was chosen as it had implemented the digital SIC using mobile technology for more than four years. Presumably, all the miners were well-versed in mobile technology usage. Thus, the population and sample for data collection were from mining employees that used the SIC in the underground division.

### **1.9 Definition of keywords**

The following are the definition of various key terms, which are commonly used throughout this thesis.

Short interval control (SIC) – This is an approach that “enables an effective plan-do-check-act (PDCA) loop for mining processes” (GMG Group, 2019).

Task-technology fit theory – This theory or model contends that a fit or alignment between characteristics of the task and information systems results in the increased usage of technology and individual performance (Goodhue & Thompson, 1995).

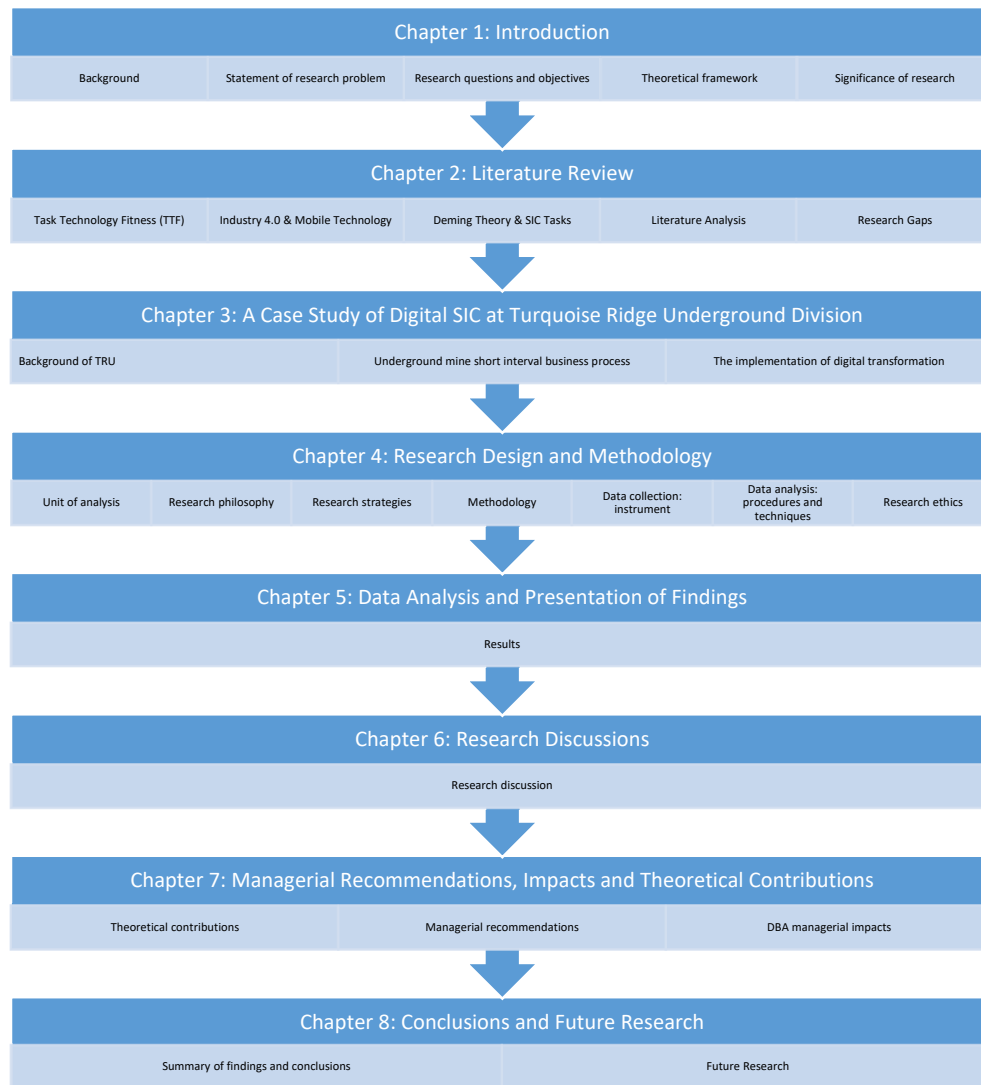
Task-technology fit (TTF) – This is the alignment between the task and information system characteristics, resulting in increased technology and individual performance (Goodhue & Thompson, 1995).

Task-technology misfit (TTM) – This is when there is a mismatch between tasks and technical characteristics, and it may occur when the attributes required to perform tasks are not prescribed in the technology (referred to as TTM – “Too Little”) or when the solicited technology is overloaded with excessive attributes to perform a task (referred to as TTM – “Too Much”)( Howard & Rose, 2019).

### **1.10 Summary**

In general, each chapter begins with an introduction that discusses the chapter's focus, its various sections and ends with a summary and a conclusion. Chapter 1 discussed the study's background, deliberating the research in the context of the mining industry's recent challenges and the driving force for DT. This investigation focused on a case study of TRU at Nevada, where a digital SIC system had been implemented using mobile technology. The concept of TTF was introduced, discussing various contexts where it was used and the gaps when applying it to mining. The chapter also described the problem statement, research aim, objectives, and research question. The theoretical framework of TTF and TTM was described at length. This chapter also discussed the methodology used for the study, as well as the study's significance, and delimitations.

Figure 1.3 shows an overview of various chapters and their sub-sections in this thesis.



**Figure 1.3: Chapter outlines of the thesis**

## CHAPTER 2: LITERATURE REVIEW

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### 2.1 Introduction

This chapter revisits the research problem outlined in the previous chapter in broader terms while simultaneously identifying the key developments to solve the problem context. It provides a theoretical background by discussing the theoretical constructs in highly influential and ground-breaking seminal academic articles and other publications related to TTF, mobile technology, and SIC tasks. This literature review section focuses on the problems addressed in these academic articles by concentrating on the problem-solving approach and methodology by explaining practical challenges, bringing out new insights, and assessing the specific writings that have influenced the topic area. The literature analysis performed for this study identified critical development, lurking issues, as well as agreements and disagreements in the areas reviewed (Boote & Beile, 2005). Upon highlighting the gap addressed in this study, hypotheses were formulated for empirical investigation. This chapter ends with a summary.

### 2.2 Re-visiting the research problem

Digital transformation is a critical strategic objective for numerous industries, including mining (CISCO, 2016). Chapter 3 describes a clear case of the Turquoise Ridge underground division that deployed a mobile technology SIC system as part of its digital transformation agenda. Many companies across various industries have spent plenty of money on technology implementations to yield lucrative benefits via improved performance and production, minimised waste and cost. According to Goodhue (1995), organisations spend millions of dollars on information systems (IS) to enhance organisational and individual performance. Although investing in technology is not a new phenomenon, many companies still fear previously failed and unfruitful technology projects that were not well adopted or delivered on time, budget and according to scope.

Extensive studies concerning IS have investigated the puzzle of IS adoption, use, fit, linkage to performance, and alignment to business strategy. These investigations have yielded several well-known IS models, including the TAM by Davis, Bagozzi and Warshaw (1989), IS success model by DeLone and McLean (1992), and the strategic alignment model (SAM) by Henderson and Venkatraman (1993), to name a few.

### **2.3 Task-technology fit and utilisation research domains**

Goodhue and Thompson (1995) asserted that studies on IS that focus on “the linkage between technology and individual performance” have been an ongoing interest. They added that two main research streams, namely utilisation and TTF, have dominated the literature in addressing this concern. They denoted that the utilisation research stream upholds that user attitudes predict utilisation based on popular studies (see Davis et al., 1989; DeLone & McLean, 1992).

In the second research stream, TTF is viewed as a predictor of individual performance. Prior studies (see Vessey, 1991; Dickson, DeSanctis & McBride, 1986) evidenced the impact of fit on individual performance. This is despite the availability of multiple models such as that of DeLone and McLean (1992). Goodhue and Thompson (1995) highlighted that the TTF construct was missing or only implicit in previous models. Furneaux (2011) asserted that the fit research stream has origins in Fiedler's organisational contingency theory (1964). The contingency theory argues for alignment or fit between organisational characteristics and circumstances to attain organisational efficacy (Furneaux, 2011). In the article entitled, “A Contingency Model of Leadership Effectiveness”, Fiedler (1964) described leadership style based on a particular scenario. This initial study by Fiedler resulted in different studies about the contingency theory. Drazin and De Ven (1985) mentioned that structural contingency theories are congruent theories, mainly because the organisational context is related to its structure. They executed empirical tests of the three approaches to fit: selection, interaction, and systems approaches. They discovered that the three forms of fit were not mutually exclusive and served as complementary to each other.

Additionally, Drazin and De Ven (1985) assessed the task-contingency theory of work design within the context of the three forms of fit. They concluded that managerial selection had significantly affected structural characteristics and a substantial correlation among setting, structure, and process. Vessey (1991) amplified the importance of aligning the representation of the problem and performing tasks to solve the problem.

Goodhue (1995) initiated the concept of task-technology fit as a user evaluation construct. He added that technology denotes one's tools to execute tasks, whereas individuals perform tasks to turn inputs into outputs. The TTF focuses on the degree to which system characteristics match user task needs, wherein higher TTF yields exceptional performance. The TTF generates better performance if users apply technology for task execution. Goodhue (1995) further argued that utilisation may be omitted from the TTF model when it is mandatory.

According to Goodhue and Thompson (1995), each research stream, namely utilisation and TTF, has several drawbacks. Hence, complete dependence on either of the two does not offer a comprehensive picture of the impact of technology on individual performance. They claimed that since utilisation is not always voluntary, the influence of performance relies on TTF instead of utilisation. A shortcoming of the fit focus model is that it neglects the fact that systems must be utilised to deliver performance.

Goodhue (1995) likened TTF to the organisational structural contingency theory, which is concerned at the organisational level, while TTF concentrates on the individual level. Goodhue and Thompson (1995) proposed a task-technology fit theory. Goodhue (1995) described that the value of technology lies in the tasks executed by users. He explained that users can evaluate the TTF of their technologies. Goodhue and Thompson (1995) proposed a TTF measure with 12 dimensions: “confusion, right level of detail, meaning, locatability, accessibility, assistance, ease of use, system reliability, accuracy, compatibility, currency, and presentation”.

#### **2.4 Technology-to-performance chain (TPC)**

Building on past IS research, Goodhue and Thompson (1995) proposed the TPC should be based on the two research streams, utilisation and TTF. The TPC model upholds that for information technology to positively affect individual performance, the technology must be utilised. Additionally, a good fit between the technology and the tasks it supports is crucial. Goodhue and Thompson (1995) asserted that their proposed model was consistent with the model initiated by DeLone and McLean (1992) and extended it by explaining how TTF helps to understand how technology affects performance. Furthermore, they claimed that the TPC offers a more robust theoretical basis to comprehend the impact of information technology on performance by being explicit about the links among constructs.

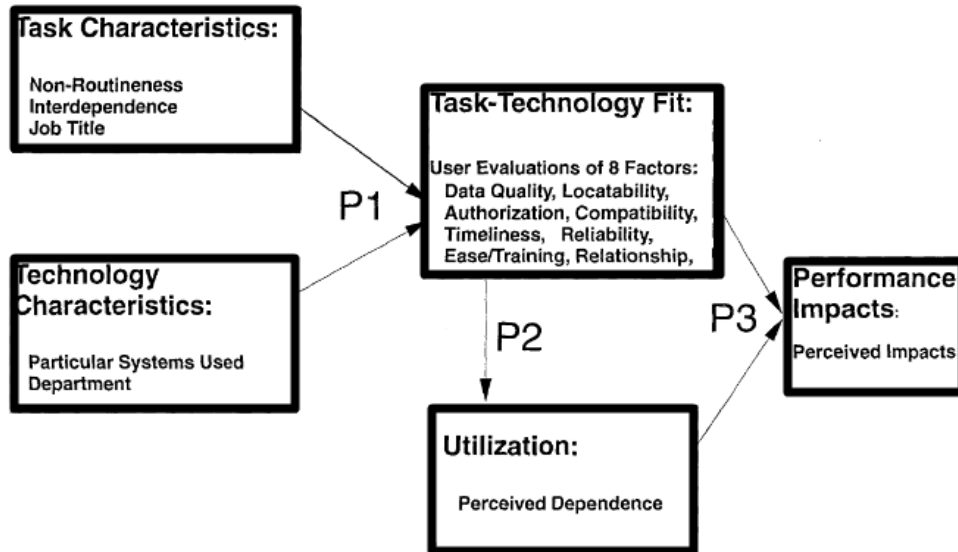
In testing the TPC model, Goodhue and Thompson (1995) recognised that TPC was difficult to test in a single study. They used portions of testing, as employed by past researchers. These included “fit” correlations among task, technology, and individual characteristics that support the link between TTF and performance, as well as support for precursors of utilisation. They tested all components of the model – from task and technology to performance impact – mainly concentrating on the role of TTF and individuals as the unit of analysis.

Goodhue and Thompson (1995) faced the challenges of testing the TPC in a narrowly controlled domain and generalising it to a global domain or testing the model in a more

generalised domain. They focused on the macro level while spanning different technologies, multiple tasks, users, and numerous organisational settings. This made the model generalisable.

The combination of research work from utilisation and TTF research streams provided the groundwork for Goodhue and Thompson (1995) in formulating the TPC model. They applied previous research measures and developed new questions that were validated via exploratory factor analysis. They ran statistical analysis to ensure that their decisions on measurements used were indeed accurate. They tested multiple correlations, including the effect of task characteristics on TTF; thus, they discovered that the most substantial impact was non-routine tasks. On top of that, they found that systems used and departments as proxies of technology characteristics were significant predictors for eight factors of TTF. Although no substantial link was noted between TTF and utilisation, they found strong support for TTF and utilisation as a predictor of performance impacts.

The paper published by Goodhue and Thompson (1995) has influenced the understanding of technology and its impact on performance. It was viewed as an evolution in task technology thinking when compared to prior models. As evidenced in their study, performance impacts are a joint function of utilisation and TTF, and neither alone is a good surrogate except under minimal circumstances. Apparently, user involvement can affect the fit of the system. With solid support, the TPC model may function as a diagnostic tool for IS and services in an organisation. The outcomes revealed that as managers began identifying specific gaps, they could discontinue/redesign systems and policies, embark on training or selection programmes, or redesign tasks to the advantage of technology potential. They called for more exploration in measuring constructs, refining TTF dimensions, and expanding the testing scope in other contexts. Following the study, many applications, refinements, and extensions have been established. For instance, Spies, Grobbelaar and Botha (2020) identified studies using this model in more than 10 industries. Furneaux (2011) explained that TTF is continually deployed and its performance benefits apply at both individual level (Goodhue & Thompson, 1995) and group level (Zigurs & Buckland, 1998), and thus it is applicable to varied levels of analysis. Figure 2.1 illustrates the TTF model proposed by Goodhue and Thompson (1995).



**Figure 2.1: Task-technology fit model**  
Source: Goodhue and Thompson (1995)

## 2.5 Classification of task-technology fit theory research

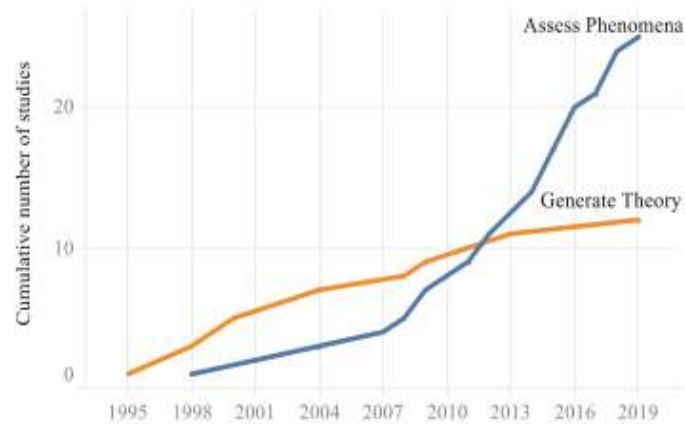
The classification of task-technology research has been a source of further investigation. Spies et al. (2020) summarised and synthesised studies that applied TTF in various industries to determine the trending progress of the TTF research area. Due to scarcity in studies that have summarised and synthesised the TTF theory, the study by Spies et al. (2020) was built on prior work performed by Cane and McCarthy (2009) (studies before 2006) and Furneaux (2011) (studies before 2010) to address why, where, and how TTF was implemented.

Spies et al. (2020) approached the study by adopting the scoping review methodology proposed by Arksey and O'Malley (2005), which was composed of five stages: (1) Identify research question, (2) Identify relevant studies, (3) Select studies, (4) Chart the data, (5) Collate, summarise, and report the outcomes.

Following the data coding, Spies et al. (2020) grouped the studies into two categories. The first high-level category refers to “Generate Theory”, which generates theory and defines/refines measurements applied for the TTF model or components. In this initial category, prior studies are summarised and followed by examining the characteristics and correlations embedded in the TTF model. Next, the second high-level category, known as “Assess Phenomena”, uses TTF to evaluate actual phenomena. The two crucial aspects in both categories are components

of TTF (antecedents to TTF and technical features) and influence of TTF. Studies that concentrate on impacts can be further grouped into two types: one group that evaluates the advantage or impact of TTF, while the other group assesses factors associated with use/intention to use the technology in light of TTF.

According to Spies et al. (2020), the two high-level categories determined the trends in the study type published over time. The focus shifted from predominantly theory to application of TTF and later, assessment of actual phenomena. Figure 2.2 illustrates the trend of studies from 1995 to 2019 for the two classifications in the TTF research domain.



**Figure 2.2: Task-technology based on category**

Source: Spies et al. (2020)

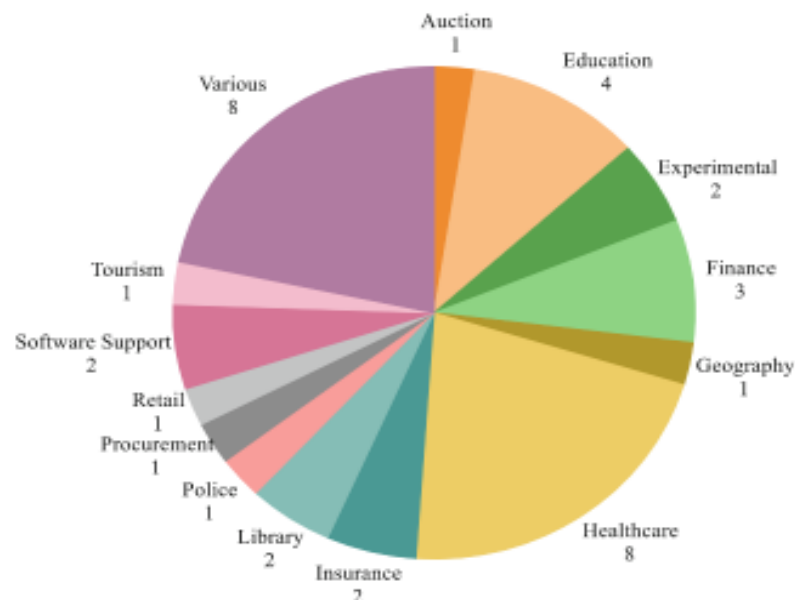
Spies et al. (2020) found that most of the studies were applied in the healthcare segment and not explicitly identified environments, wherein the execution of tasks varied substantially. The wide applicability of TTF in multiple environments suggests interesting future endeavours in terms of similarities and variations in TTF usage. Essentially, Spies et al. (2020) highlighted the potential of using the TTF theory in academia and industry domains that apply differing technologies and settings. However, the study by Spies et al. (2020) had some shortcomings, such as articles retrieved from a single database that could omit other pertinent work.

According to Spies et al. (2020), most of the research work concentrated on examining an actual phenomenon or developing a theory across various settings, particularly the healthcare segment and including the mobile technology field. Notably, the study by Spies et al. (2020) has deciphered the deployment of TTF, thus facilitating future work to assess TTF from other angles.

The study by Spies et al. (2020) has aided researchers in comprehensively deciphering the research streams of TTF and identifying potential research areas. These research streams include analysing various TTF studies to identify trends in the methodology used across multiple technologies, applications, and setting categories. They prescribed future work to look into the influence of technology on a system.

## 2.6 Applications of the TTF theory

The TTF theory has been impactful in understanding the role of technology and task characteristics and impact on individual performance. Besides, the TTF has been used extensively in different industries. Chart 2.1 illustrates the research papers published in various sectors.



**Chart 2.1: Task-technology fit application by industry**

Source: Spies et al. (2020)

The healthcare segment, for instance, was examined by Lin (2014) through the lens of TTF. The study probed organisational readiness by assessing the efficacy of mobile nursing information systems (MNIS) and its application by nursing staff to accomplish daily clinical tasks. The study involved clinical professionals and deployed a 25-item questionnaire measured using the Likert scale. Lin (2014) carried out both measurement and structural model assessments. The study outcomes revealed a more significant impact of technology-individual fit on MNIS than TTF. The authors found that organisational readiness significantly

influenced MNIS. The study added to the body of knowledge on the subject by classifying TTF into two constructs – TTF theory itself and technology individual fit.

According to Spies et al. (2020), many studies regarding TTF theory have focused on various segments and industries, including education (D'Ambra et al., 2012; McGill & Hobbs, 2007; Robles-Flores & Roussinov, 2012), engineering (Dare-Abel, 2014), insurance (Kishokumar & Thiyagarajan, 2015), finance (Musyaffi & Muna, 2020), and manufacturing (Mikalef et al., 2019).

Interestingly, few studies had assessed TTF within the mining industry. Swanson and Bellanca (2018) performed a notable pilot study to explore the TTF Assessment for Mobile Proximity Detection System (Mobile PDS) within the coal mining context. They described the implementation of new mining technologies to enhance both safety and efficiency in mining, in which TTF had a major role. Their research focused on task exploring fit on Mobile PDS, wherein they argued that fit is another factor that affects unsafe mining practices. They researched the fit between Mobile PDS for mobile machines and underground coal mining. Using both the TTF and mixed method approaches, they targeted mine leaders at two underground coal mines and completed the surveys and participated in guided group discussion sessions. Swanson and Bellanca (2018) reported preliminary findings that are useful for further research work. Essentially, their study shed light on a rarely discussed topic of TTF within the mining context.

## **2.7 Arguments for and against the task-technology fit theory**

As discussed, the TTF theory has had broad applications in different industries. It is now generally agreed that the fit between task and technological characteristics significantly influence utilisation and performance outcomes. Some notable studies that agree with this viewpoint include well-known authors (Abdillah & Saepullah, 2018; D'Ambra et al., 2012).

Abdillah and Saepullah (2018) examined the applicability of the SIMDA Finance 2.7 program for local governments in Indonesia. The hypothesis testing of the structural model indicates that task characteristics influence the performance of technological tasks. They discussed that these findings are consistent with previous studies showing that the purpose and accessibility of the technology are linked. Their study found that job characteristics and work impact are related to each other.

D'Ambra et al. (2012) assessed the TTF model to explore the interrelationships of e-books, information needs of academics, and “ease”. Their results of confirmatory factor analysis “supported the overall TTF model which reflects significant positive impact of task, technology, and individual characteristics on TTF for e-books in academic settings”. The study also confirmed a “significant positive impact of TTF on individuals' performance and use, and the impact of using e-books on individual performance” (D'Ambra et al., 2012).

Although there is widespread acknowledgment that technological characteristics have a significant influence on TTF, as discussed by many other researchers (Barki, Titah & Boffo, 2007; Dishaw & Strong, 1999; McGill & Klobas, 2009; Staples & Seddon, 2004; Yu & Yu, 2010) that agree with Goodhue and Thompson (1995), disagreement remains about these results. Many disagreements have been forwarded by the research work of many authors (Kademeteme, Kalema & Pretorius, 2015; Lam, Cho & Qu, 2007; Strong, Dishaw & Bandy, 2006).

Lam et al. (2007) examined perceived IT beliefs, job task-technology fit, and self-belief to learn more about the influence of technology adoption in hotels in Hangzhou, China. Their study showed that technology did not result in a positive attitude towards IT. They explained that these results contradicted previous studies (Dishaw & Strong, 1999; Goodhue & Thompson, 1995). It is believed that while many individuals feel they would be able to meet the task requirements, this could be because they lack both the know-how and the skills required to complete it. Nonetheless, the results of their study suggests that task-technology influences attitudes informing IT beliefs.

Strong et al. (2006) undertook a study to understand software users' habits better, using various forms of modelling, modelling estimates, and conducting new research. Their study used the computer self-efficacy (CSE) construct suggested by Berthon et al. (2002) as part of an extended a TTF model. This experiment looks at business students' usage of modelling tools. Thus, this study shows that CSE, which means users' beliefs power the model, results in a greater explanatory power (fit) than a TTF model that solely consists of task characteristics and it has a direct impact on usage but no significant interaction. Strong et al. (2006) asserted in contrast that according to a lot of theory, interactions among personal characteristics aren't productive (Goodhue, 1995). Thus, they argued that Goodhue (1995) reports no significant inter-level interactions.

## **2.8 Extensions/Refinements of TTF**

Despite the vast use of TTF, many IS researchers agree that TTF needs extension or refinement to adapt to a broad range of contexts (Howard & Rose, 2019; Lee, Cheng & Cheng, 2007). The extensions include integrating TTF with other models and incorporating other theoretical constructs. Meanwhile, the refinements are concerned with the better model operation and the development of new measures. A few relevant extensions and refinements of the TTF model undertaken in this present study are discussed in the following sections.

### **2.8.1 Unified theory of acceptance and use of technology (UTAUT) and task-technology fit (TTF)**

In Arabic countries, Iyoubi and Yamin (2019) applied the TTF in the public sector industry and focused on a population that comprised government staff. They integrated the TTF model with the UTAUT. Upon adopting the positivist research philosophy, the questionnaire and structural equation modelling (SEM) were used for data collection and analyses, respectively. As the context was limited to Arabic countries, the outcomes lacked generalisability. Their study offered several theoretical and managerial implications based on positivist research philosophy with a cross-sectional time horizon. First, the study contributed to the body of knowledge for UTAUT and TTF by explaining causes that developed intention among employees to adopt information technology, which enhanced their job performance. Second, the study revealed that "employee intention to adopt technology is jointly predicted by performance expectancy, effort expectancy, social influence, facilitating condition, task characteristics, technology characteristics, and innovation valance". Lastly, the managerial implication included a suggestion on the importance of using a performance matrix to identify employee intention to adopt the technology.

### **2.8.2 Task-technology Fit (TTF) and task-technology misfit (TTM)**

Although TTF has been applied across various industries, Howard and Rose (2019) asserted that the TTF theory needs refinement and extension. First, many studies using the TTF theory do not conceptualise it according to the original theory. Second, issues related to TTF operationalisation exist due to confounds in conceptualisation and the use of inaccurate scales. Third, many studies emphasised direct effects when the theory itself proposes moderating and mediating effects. Finally, the authors highlighted that many studies focused on "good" TTF while neglecting TTM. The oversight of "misfit" stems from the assumption that misfit is a problem. On top of the issues raised above, past studies conceptualised TTF inconsistently with

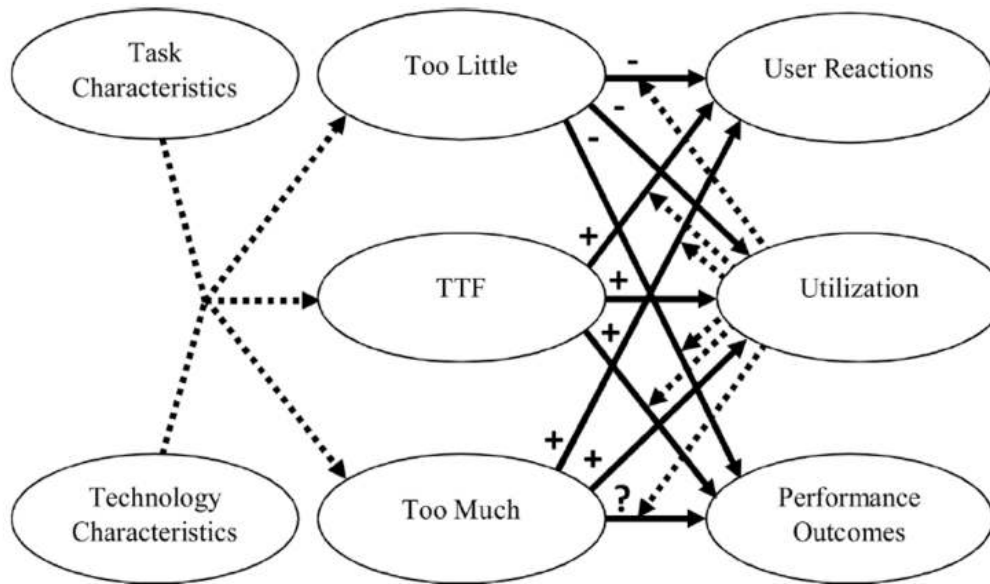
the TTF theory, omitted the variances between TTM and TTF, and developed scales that failed to measure TTF accurately. The failure of previous outcomes to reflect the true nature of TTF has hindered a clear understanding of the TTF theory.

Howard and Rose (2019) performed a four-study process to develop two satisfactory scales. Hence, two empirical studies were executed to confirm the three-dimension conceptualisation of TTM and TTF based on the TTF theory that led to the initiation of two new TTF measures. Next, the two measures were refined and extended into a three-dimensional (3D) TTF conceptualisation fit for a broader TTF framework. It signified that some task and technology features had an interactive impact on TTF generation, but the impact was nuance.

Howard and Rose (2019) conducted the first four studies similar in design and recruited participants from Amazon Mturk with monetary reward. The exploratory factor analysis was deployed to develop the scales and to identify factors used for the measures. The selection of top factors led to the formulation of the 3D TTF/M scale. Ensuing, the fifth and sixth studies embedded time gaps. Scales proposed by Howardson and Behrend (2016) were adopted to measure user perceptions. Howard and Rose (2019) used confirmatory factor analysis to determine the loading factors on latent variables. Correlations were proposed to understand the relationships among the constructs (gender and age were controlled for all correlations).

Participants who did not pass the attention test were omitted from data analysis. The listwise deletion approach was deployed to address missing data.

Howard and Rose (2019) reported the following outcomes involving TTF, TTM, and user reactions: (1) TTF had a significantly positive and strong link with user reactions, (2) Too Little displayed a significantly negative and strong relationship with user reactions, and (3) Too Much exerted an insignificantly negative and strong correlation with user reactions. Figure 2.3 illustrates the refined task-technology model.



**Figure 2.3: The refined task-technology model**

Source: Howard and Rose (2019)

Next, Howard and Rose (2019) registered findings among TTF, TTM, and utilisation: 1) TTF displayed a significantly positive and strong link with utilisation, 2) TTM – “Too Little” exerted a significantly negative and strong correlation with utilisation, and 3) TTM – “Too Much” was insignificantly negative and strongly correlated with utilisation. Apparently, TTF showed a similar impact on user reactions and utilisation.

The discussion on interactive effects by Howard and Rose (2019) supported TTF conceptualisation and operationalisation. They highlighted the significance of three task and technology characteristic pair interactions in predicting TTF measured by TTF/M and TTF scales. Two of the pair interactions appeared essential in predicting Too Little, while one pair interaction was significant for predicting Too Much. Meanwhile, two direct effects emerged as significant: 1) Technology variety impact on TTF, and 2) Too Much on technology feedback. According to Howard and Rose (2019), although the outcomes exemplified that certain task and technology characteristics had impacted TTF production, the impacts were nuanced. For example, some features displayed interactive impacts that predicted TTF alone, while other only predicted TTM, and some predicted both TTF and TTM.

Apart from revealing some empirically validated ideas on TTM, which were new within the research domain, the study initiated new measures for TTF application.

Howard and Rose (2019) asserted that future work should focus on testing relationships of fit using the proposed scales, including user characteristics and replication of their results with other research approaches/designs (e.g., time-gap and panel studies or elongated temporal gap between measurements). Moreover, an experimental design was prescribed to assess the causal effects of TTM and TTF. The next section discusses other theories and studies reviewed in this present study.

## **2.9 Related work**

The previous section discussed the TTF model, including its varied refinements and extensions extensively. This present study focused on the TTF and TTM construct proposed by Howard and Rose (2019). The research objectives were focused on applying both TTF and TTM constructs to SIC tasks using mobile technology. The following sections cover the SIC and the mobile technology background.

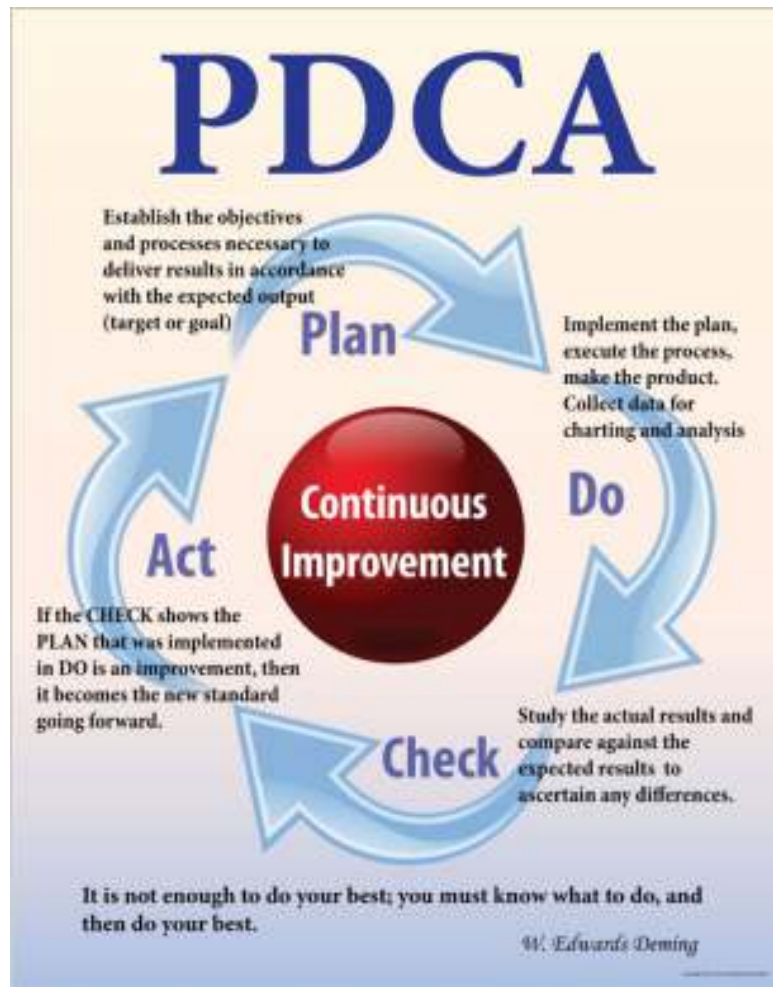
### **2.9.1 Short interval control (SIC) process**

According to GMG Group (2019), SIC denotes the structured process involving the review of data at short intervals during the shift to address real-time deviations. Thus, SIC as a formal framework supports the management of shift tasks and evaluates actual production compared to planned output (Savit et al., 2018). This process enables supervisors to enforce mid-course corrections to improve the overall production efficacy and efficiency during a shift (Savit et al., 2018). As underground mining variations are often long (12 hours), review during intervals may range between once every six hours and once every hour or less (GMG Group, 2019).

Both Howes and Forrest (2012) and GMG Group (2019) agreed that SIC is often deployed in the manufacturing industry. The latter claimed that SIC is new to the mining context due to unpredictable working conditions. Cutting-edge technology and communication infrastructure installed in underground settings have generated vast opportunities to implement SIC in managing shifts. Companies with SIC demand multiple components to be integrated with business strategy, culture, and operation (GMG Group, 2019).

Howes and Forrest (2012) discussed the SIC case study of Chelopech Mining EAD (CMEAD), where SIC was used in an underground mine to enable efficient operations with shift time and use of assets. The GMG Group (2019) listed the beneficial process of SIC that adjusts real-time operation based on real condition to attain short-term planning and shift goals, besides slashing costs and enhancing productivity for mining business. It was stipulated that SIC

concentrates on enhancing environmental performance, mine safety, and the overall equipment effectiveness, apart from optimising processes and reducing burden shouldered by supervisors. Howes and Forrest (2012) explained that the feedback loop during the SIC process, which compares production tracking against expected production, enables decisions and intervention actions including dispatching resources to minimise deviation from the target goal. GMG Group (2019) added that SIC targets a continual enhancement loop for minimal waste and improved productivity in the mining segment by enabling the PDCA loop (see Figure 2.4).

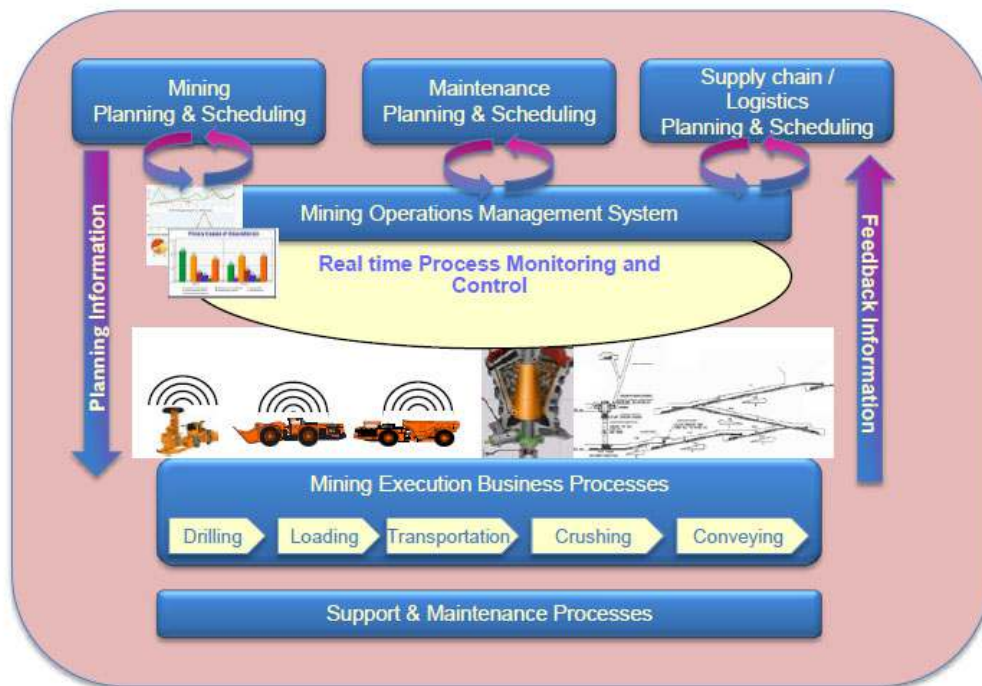


**Figure 2.4: The PDCA loop**

Source: Lean Manufacturing Posters (2021)

The GMG Group (2019) claimed that the PDCA loop is well received in the manufacturing domain as an effective continuous improvement loop that examines a process and determines the following: enhance the process (plan), assess the plan (do), evaluate the test (check), and implement the improvement (act).

Goodhue (1995) defined tasks as actions executed by individuals that turn inputs into outputs. Goodhue and Thompson (1995) asserted that tasks with characteristics could be denoted as routine, non-routine, interdependence, etc. In this present study, task characteristics reflected tasks carried out as part of the SIC process. The GMG Group (2019) claimed that critical tasks comprising SIC tasks include planning, situation awareness, resource management, and operational decision making. Figure 2.5 presents the mining planning to execute the business process loop, which illustrates a range of SIC tasks.



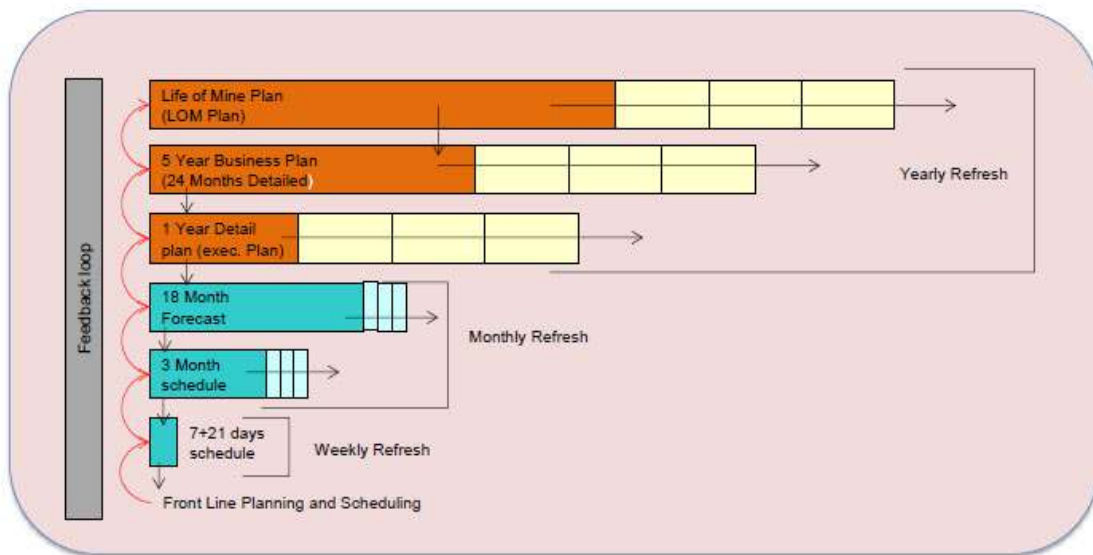
**Figure 2.5: Mining planning to execute business process loop**

Source: Howes and Forrest (2012)

The planning (tactical and strategic) tasks equip mine operators with trustworthy and the latest information to enable adjustment in plan from a fixed set-point. This permits the leaders to meet tactical and strategic goals while holding operators accountable. Awareness of the situation enables the control room to locate assets and team members during each shift to monitor real-time task progress. The resources (e.g. personnel, equipment, and assets) can be detected by the control room, as permitted by the resource management. Operational decision-making, which offers knowledge about tactical and strategic priorities, enables the operational team to alter or reprioritise targets when an unanticipated event occurs.

Howes and Forrest (2012) depicted that real-time data is vital for underground mining that involves many applications, such as ventilation monitoring, equipment, personnel location tracking, fixed equipment control and monitoring, and centralised blasting and monitoring. They claimed that SIC works with a central command centre, where real-time data are gathered and tracked against assigned tasks for a shift. The control room supervisor can intervene upon deviation of an assigned task based on central monitoring and control information. The central aim is to complete as much work as scheduled in the shift to maximise resource use.

The GMG Group (2019) explained that the SIC process is multi-stakeholder by nature that involves various actors with numerous roles and responsibilities. The key player is the shift supervisor, who is responsible for the timely execution of tasks, top-notch product quality, and workplace safety. Figure 2.5 above shows mining planning and scheduling as the vital aspect of the mining business process loop, while Figure 2.6 below portrays SIC planning and scheduling with varied stages: short-term planning, weekly planning, shift scheduling, as well as in-shift and post-shift reviews.

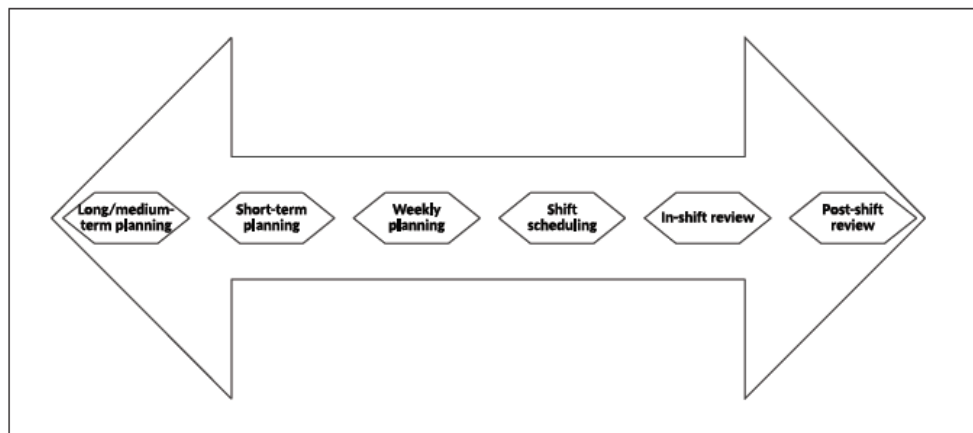


**Figure 2.6: Mining planning cycle**

Source: Howes and Forrest (2012)

Before discussing short-term planning, it is necessary to revisit where it begins. Excluded from GMG Group's generic SIC model (2019), long-term planning initiates the mining planning process. The GMG Group (2019) claimed that engineers and specialist geologists undertake the design and planning activities to set viable targets in line with the mining investment. These

targets, which are crucial to support the mining efforts, clearly identify the capital expenditure and mining processes. Meanwhile, GMG Group (2019) described that the short-term planning process is built from long-term planning. It is at that stage that the SIC processes come into play. Short-term planning involves identifying the sought resourcing, interactions that must be controlled, and downstream needs in meeting long-term plan goals (e.g. grades). The SIC starts upon determining both conditions and resourcing, whereby each action may affect short-term plan delivery. The GMG Group (2019) added that the SIC process embeds regular assessment progress against a known plan, besides arriving at future actions based on the assessments. Upon identifying risks at the early stage, effective measures may be devised to address any unexpected event. In Figure 2.7, the double arrows denote the bi-directional flow of information (GMG Group, 2019). Each decision made in this stage has implications for the stages before and after in the planning chain (GMG Group, 2019).



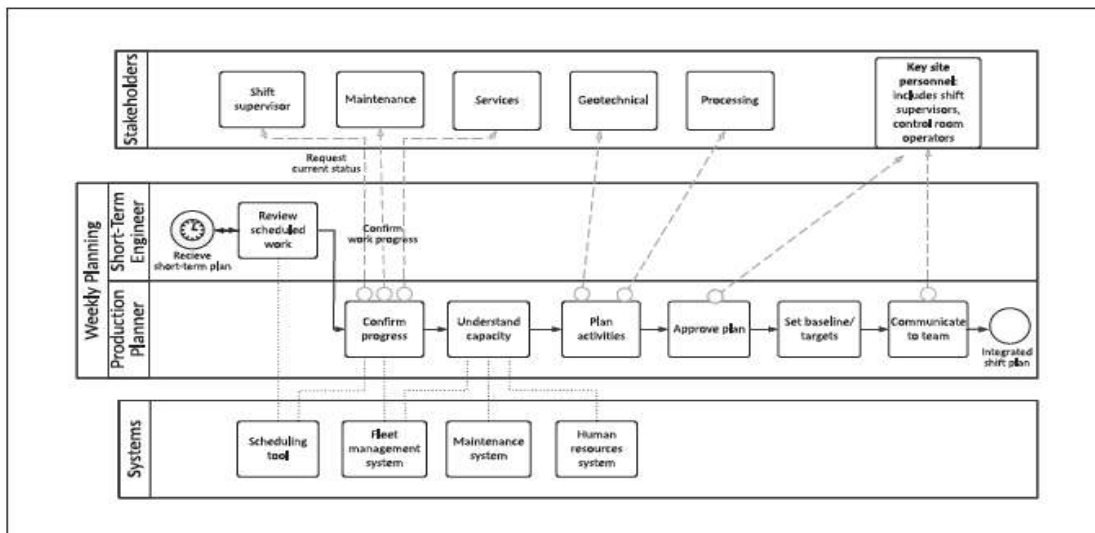
**Figure 2.7: Mine planning and operational control chain in short interval control environment**

Source: GMG Group (2019)

Weekly planning is the next stage after short-term planning. The GMG Group (2019) mentioned that the short-term plan detects the mining venue and the sought progress to meet mining aims. Weekly planning turns engineering resources into short-term plan tasks, wherein the assigned resources (equipment and personnel) can start working guided by timeline until completion. When short-term plans are expanded to tangible activities, the planner may coordinate with other mine units, such as processing, maintenance, geotechnical, and services, to devise an efficient plan within the assigned timeframe (GMG Group, 2019). Despite the exclusion of weekly planning from the SIC process, it sets the baseline for production timing

and quantities to measure task completion. A weekly plan that is solid ensures the success of the short-term plan and that it is on track to attain a long-term plan. Weekly planning starts when the short-term plan is released and concludes with an actionable schedule that supports all mining operation facets to achieve their respective goals (GMG Group, 2019).

Figure 2.8 displays a workflow to devise a weekly plan based on a short-term plan to cater for 3-6 months of tasks, besides determining the crucial stakeholders, personnel, and systems in the process (dashed arrows = interaction among people and dotted lines = connection with systems) (GMG Group, 2019). The main actors in the weekly planning process are the production planner and short-term mining engineer, who schedule weekly activities based on short-term plans and report to stakeholders about work progress (GMG Group, 2019). The production planner should match the targets with available stockpiles (capacity), equipment (with varied rates), and crew to devise a viable plan. Changing a machine or its type affects the ability of the crew to meet the targets outlined in the plan. The production planner must collaborate with other units to ensure the availability of resources to execute the weekly plan successfully, or the plan must be revised based on available resources (GMG Group, 2019).



**Figure 2.8: Weekly planning workflow**

Source: GMG Group (2019)

After identifying the available resources, the activities are reviewed and adjusted to ensure the maximum likelihood of attaining the targets (GMG Group, 2019). The critical site personnel should walk through the weekly plan to ascertain that all activities are correctly planned and attainable. After gaining agreement from all parties to hinder conflict of interest, a baseline is

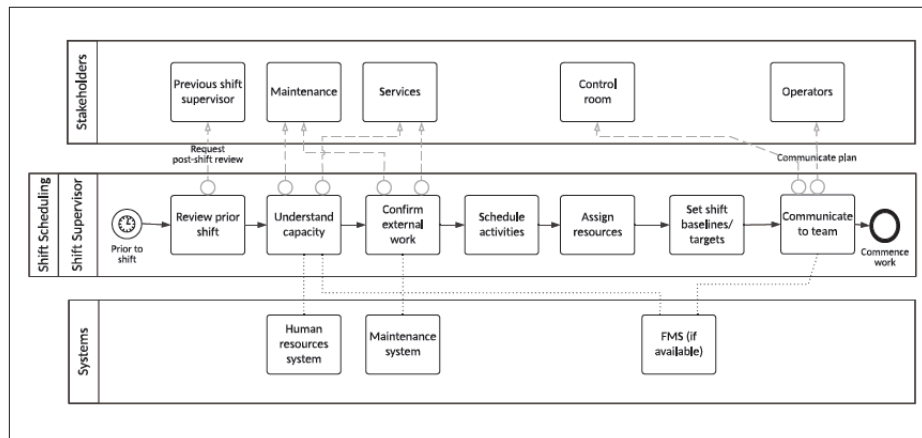
fixed to monitor the progress and address any deviation from the plan. The targets must be visible to system users to facilitate performance tracking (GMG Group, 2019). Upon setting the baseline, the weekly schedule is communicated to control room operators, stakeholders, and shift supervisors so that they too can review the plan. Once accepted, the operational crew can deploy the plan (GMG Group, 2019). Table 2.1 lists the activities of the main actors during the weekly planning process, along with the critical inputs, outputs, and issues that should be weighed in (GMG Group, 2019).

**Table 2.1: Weekly plan activities**

Action	Description	Inputs and Outputs	Issues
Receive short-term plan	The short-term engineer notifies the production planner that a short-term plan has been updated, refined, and approved and is ready to be reworked into the weekly plan	Input: The short-term plan	Understanding the contents and level of detail in the short-term plan will inform construction of the weekly plan
Review scheduled work	Outline the work required to achieve each task in the schedule	Output: A set of activities that can be assigned to various resources	Activities might not be standardized or could be subject to change based on conditions
Confirm progress	Confirm the current status of each activity (not started, on track, behind schedule, or ahead of schedule); provide progress/status reports to stakeholders	Output: A schedule that accurately reflects current progress in the mine	If progress is tracked manually, the information will need to be verified
Understand capacity	Liaise with other sectors of the mine to ensure that the resources necessary to achieve the weekly plan are available	Inputs: Maintenance plan, operator availability (subject to leave and overtime), current stockpile balances, service schedules Output: Schedule of achievable activities based on available resources	Incorporating the service crew plan is key to delivery because their work can be lengthy and cause delays on multiple fronts
Plan activities	Review all planned activities, including those of non-mining crews, and adjust the schedule to maximize the chance of delivering on target	Output: An expanded mining schedule that accommodates all other relevant schedules	
Approve plan	Complete a structured walkthrough of the plan with key site personnel to get agreement that all activities have been correctly planned and the plan is achievable based on current information	Output: Approved weekly plan	All parties must agree to the plan, otherwise it is likely to be negatively impacted by (or will negatively impact) the activities of other sectors
Set baseline/targets	Set baseline with visible targets to facilitate performance tracking and identify and mitigate deviations early, ensuring that the plan is followed and targets are met. A baseline also records key metrics (e.g., KPIs).	Output: A plan that can be tracked visually to monitor progress, identify risks or deviations early, and facilitate mitigation actions	Targets should be visible to system users
Communicate to team	Communicate the schedule to all stakeholders, especially shift supervisors and control room operators	Output: An agreed schedule with clear activities, targets, and timelines	
Provide weekly plan to operations	All key personnel accept the schedule and it is ready for operational crews to implement	Output: A list of deliverables driven by the weekly and short-term plans	

Source: GMG Group (2019)

After weekly planning, the next step in the SIC process is shift scheduling, which entails assigning resources to tasks for the upcoming shift (GMG Group, 2019). Figure 2.9 displays the shift scheduling workflow. The flow starts when the next shift supervisor begins planning the shift and ends with the planned, prioritised, and resourced plan. The supervisor can prepare a schedule for blasts if the window is present between shifts, or else the shift schedule must be completed before the previous shift ends (GMG Group, 2019). Besides establishing clear communication between supervisors from the last and the next shifts, it is important for all those involved to comprehend the planned schedule. Any unanticipated activity highlighted in the previous shift demands rescheduling to embed the new activity. The supervisors and control room operators must be careful during shift scheduling to ensure clear communication and hinder the loss of information while communicating via radio (GMG Group, 2019).



**Figure 2.9: Shift scheduling workflow**

Source: GMG Group (2019)

Table 2.2 lists the activities of the main actors during the shift scheduling sub-process, along with the critical inputs, outputs, and issues that demand consideration.

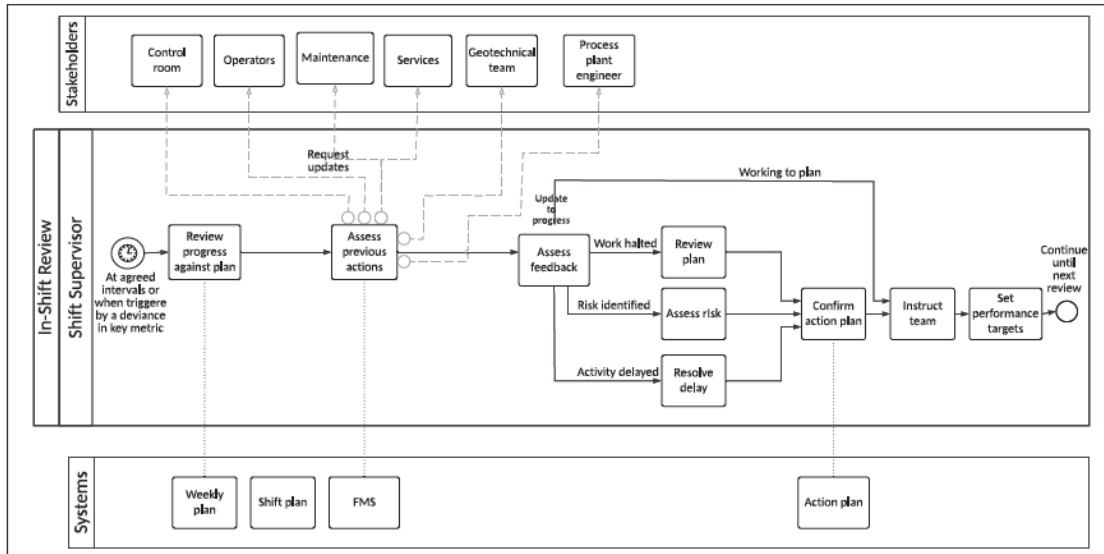
**Table 2.2: Shift scheduling activities**

Action	Description	Inputs and Outputs	Issues
Review prior to shift	Shift supervisor reads the post-shift review from the previous supervisor and checks prior shift performance, with particular attention to: <ul style="list-style-type: none"> <li>– Progress to plan</li> <li>– Unfinished activities</li> <li>– Resource performance</li> <li>– Conditions encountered</li> <li>– Working locations of other crews (e.g., services)</li> <li>– Activities moved to the upcoming shift</li> </ul>	Input: Progress/performance report from the previous shift; comments from the previous shift	If shift scheduling must take place before the end of the previous shift, the shift supervisor might not have the latest information
Understand capacity	Shift supervisor checks reports on: <ul style="list-style-type: none"> <li>– Equipment either in or expected to be in maintenance</li> <li>– Location(s) of available replacement equipment</li> <li>– Operators assigned to the shift and limitations on their time (e.g., overtime operators whose time might be limited by law or contractors working the shift)</li> <li>– Workplace safety (location inspections and incident reports)</li> </ul>	Inputs: Equipment status report, operator status report, location inspections, hazard incident/mitigation report	Some or all of this information might not be available at planning time Location inspections might be a statutory requirement A failed location inspection can block access to a location
Confirm external work	The shift supervisor must collect and incorporate data from: <ul style="list-style-type: none"> <li>– Maintenance, both scheduled and unscheduled</li> <li>– Services, to understand where to send machines based on services availability or repairs needed</li> <li>– Other mining activities such as exploration drilling (likely to be controlled by the geologists)</li> </ul>	Inputs: Maintenance schedule, services schedule, and other external schedules (e.g., diamond drilling schedule)	If external work affects location availability, the shift supervisor will need to access additional work areas and activities to make up for the loss
Schedule activities	The shift supervisor creates a list of work tasks for each operator on the shift based on shift targets. This list includes notes about task prioritization (based on earlier decisions), such as if a machine is due for maintenance mid-shift and should be used first	Input: A list of all tasks scheduled for the upcoming shift Output: A list of all shift tasks assigned to each operator, prioritized based on external factors and weekly targets	Insufficient resources might prevent work from being completed
Assign resources	The known list of resources is used to match resources to tasks that are needed for the upcoming shifts. Inventory to support activities is planned to ensure it is available as required. In a more mature environment, assigning operators can also include validation of operator competencies. Maintenance may also advise prioritizing certain machines based on engine hours	Input: Full list of all available resources, list of all shift tasks assigned to each operator Output: Complete task list (each with a start time, duration, and end time) for the upcoming shift, with all tasks resourced (operators and equipment) according to availability and priority	
Set shift baselines/targets	Baselines are chosen to allow staff to monitor progress and assess if the schedule conforms to the plan. Stretch targets set against KPIs can also be used to communicate shift and plan goals	Input: Complete task list of assigned work for the upcoming shift Outputs: A shift baseline that confirms the planned tasks and defines targets (optional) for the work in the upcoming shift	
Communicate to team	Shift supervisor communicates the plan to all operators and control room personnel. If a FMS is present, the tasks (and associated comments) may be sent directly to each machine	Output: Assigned tasks are communicated to the team	

Source: GMG Group (2019)

In-shift reviews are crucial in the SIC process (GMG Group, 2019). Figure 2.10 portrays the in-shift scheduling workflow. The scheduled tasks are regularly reviewed to monitor work progress, thus meeting the demand for control and response. The outcome should minimise waste and enhance productivity. In mines with SIC, in-shift reviews take place in regular and predetermined intervals throughout the shift. The operators and supervisors can do the reviews

or if the deviation is detected. Reviews can occur while changing shifts at less mature sites with actions deployed during the next shift of the future plan.



**Figure 2.10: In-shift scheduling workflow**

Source: GMG Group (2019)

Review meetings typically occur via radio contact due to an inaccessible work site for the review team (GMG Group, 2019). Both data quality and update frequency are crucial when inspecting work progress. For fundamental operations, data accessible with manual communication denotes the quality of input from the operator; data is typically retrieved from shift logs and manual observation. Mine sites with task management instruct the operators the assigned tasks complete with fixed time (expected duration and deadline), quantity (tonnes of ore), and quality (grade) (GMG Group, 2019). Task assignment and adjustments/updates are informed to the operators via console/tablet-based communication system with advanced operations. Table 2.3 lists the in-shift scheduling activities that reflect the in-shift review process, along with key inputs, outputs, and issues that should be considered (GMG Group, 2019).

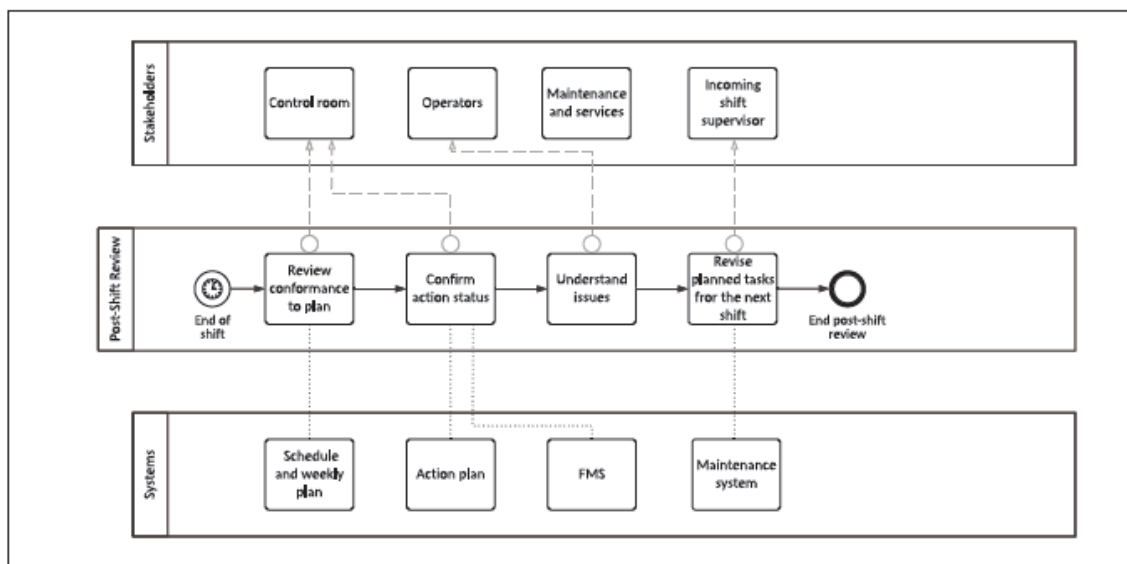
**Table 2.3: In-shift scheduling activities**

Action	Description	Inputs and Outputs	Issues
Review safety	Shift supervisor reviews safety reports, including incidents (actual and near misses) and upcoming activities that involve risk and creates an action plan for any items that require a response	Input: Safety feedback Output: Action plan	Timely communication of safety concerns affects how long it takes for the issue to be mitigated
Review progress against plan	Shift supervisor checks status reports from crew and equipment and assesses performance since the last meeting, with particular attention to <ul style="list-style-type: none"> <li>– Progress to plan</li> <li>– Unfinished activities</li> <li>– Resource performance</li> <li>– Conditions encountered</li> <li>– Working locations of other crews (e.g., services)</li> <li>– Activities that have been moved to the upcoming shift</li> </ul>	Input: Status reports from the crew, weekly plan, shift plan Output: List of discussion items for review meeting (if applicable)	If equipment is operating outside of communication areas, it might not be able to transmit status reports for review
Assess previous actions	Review changes made to the weekly and/or shift plan during the previous review meeting to determine if the changes resulted in the desired outcome Identify and analyze main delays during the work period to see if there is a pattern	Input: Action plan (output) from the last in-shift review Output: Assessment of effectiveness of mitigation actions	
Assess feedback	Review feedback from the mine to ensure that work is being performed according to plan. Potential responses are: <ul style="list-style-type: none"> <li>– Work is proceeding according to plan</li> <li>– Work at a location has been halted</li> <li>– A risk has been identified that might require mitigation</li> <li>– A planned activity has been delayed</li> </ul>	Input: Feedback from various sources (e.g., radio calls from the operators, comments on work cards, and updated data from a FMS)	Feedback data must be as current as possible to identify issues early (SIC). Outdated data may result in wasted effort
Work halted: Review plan	Shift supervisor assesses the reason for the halt, its impact on the schedule, and whether the equipment or operator assigned there needs to be reassigned to a new location. All effort must be made to resolve the issue in the current location and adhere to the shift schedule	Input: Feedback from work station; confirmation of location downtime	Only look for alternative work locations if a resolution at the assigned location is not possible
Risk identified: Assess risk	Shift supervisor assesses the impact of the risk, categorizes the risk based on urgency, and assigns risk mitigation. Possible risks are: <ul style="list-style-type: none"> <li>– Risk to plan</li> <li>– Risk to personnel</li> <li>– Risk to equipment</li> <li>– Risk to the location or related location</li> </ul>	Input: An identified risk Output: An action item to mitigate the risk	
Activity delayed: Resolve delay	Shift supervisor reviews the delay with the appropriate personnel and develops a mitigation plan to resolve it, with focus on maintaining the shift schedule and getting back on plan. Going to another location or moving activities to the next shift should only be considered if staying on schedule/on plan is not possible	Input: An identified delay Output: A mitigation plan for the delay	
Confirm action plan	Shift supervisor confirms an action plan that addresses all stoppages, delays, and risks. Any authorized additional work is added to the shift plan and the impact of that work assessed. Any costs of additional or emergency tasks are recognized and the details of the change are documented	Input: Mitigation items from previous tasks, weekly plan, shift schedule, progress reports Output: Action plan to form the basis for continued in-shift activities. To be reviewed at the next meeting	
Instruct team: Communicate plan	Communicate the new action plan, any new instructions, and associated relevant information to all personnel (e.g., control room operator, equipment operators) who are affected by the changes	Input: Action plan Output: Instructions to personnel	Note: This change can be communicated by any senior member of the team
Update performance targets	Review planned activities for the next working period and confirm they are achievable and in line with targets; if necessary, update the targets to reflect the change. Does not change any baselines; baselines are only modified/set as required for performance monitoring	Output: Updated rates and targets	

Source: GMG Group (2019)

The review is meant to support better decision-making and performance for the next shift, apart from informing the process of shift scheduling. Nearing shift end, the shift supervisor reviews the end-of-shift data, which include arising issues during shift, performance level, in-shift

action plans, as well as progress comparison between weekly and short-term plans. Next, the task list and report are prepared for the next shift. The report informs all completed tasks, inventory list, instructions, service and maintenance needs, location of critical resources (equipment), and any other vital information (GMG Group, 2019). The post-shift review validates both decisions and work executed during the just-completed shift using end-of-shift data to make informed assessments and decisions on future plans (GMG Group, 2019). This identifies the viability of shift schedule, weekly plan, and short-term plan aspects based on key performance indicators in assessing performance (GMG Group, 2019). Figure 2.11 presents the post-shift review workflow.



**Figure 2.11: Post-shift review workflow**

Source: GMG Group (2019)

The next shift supervisor reviews the report at the start of the shift scheduling process (GMG Group, 2019). The outgoing shift supervisor updates the action plan, identifies emerging issues, determines their cause, and assesses if shift schedule, weekly plan, or short-term plan demand modification – without changing the baseline (GMG Group, 2019). The targets may be amended, and based on the SIC process, information gathered from each post-shift review aids the system to react quickly based on circumstances. Table 2.4 lists the activities undertaken during the post-shift review process, along with their key inputs, outputs, and issues for consideration.

**Table 2.4: Post-shift review activities**

Activity	Description	Key Inputs and Outputs	Issues
Review conformance to plan	Shift supervisor for the just-completed shift compares the shift schedule to the weekly and short-term plan with respect to performance and identify issues requiring review	Input: Weekly and/or short-term plan Output: Issues list for review	
Confirm action status	Shift supervisor compares the shift schedule to the latest action plan, confirms progress, and identifies required revisions	Input: Action plan Output: Updated action plan	
Understand issues	Shift supervisor reviews issues arising during the recently completed shift and determines the cause of each issue: – Failure to achieve progress to plan – Unfinished activities – Resource performance – Unexpected conditions – Other crews on site (e.g., services)	Input: Issues list Output: Updated action plan	
Revise planned tasks for the next shift	Create a task list for completion during the next shift that includes: – A review of each task with any necessary instructions/feedback. If a FMS with rate-based tasks is in use, review rates achieved or, if planned rates are not being achieved, make changes to better reflect current conditions if possible. – An up-to-date list of key equipment locations (a FMS can provide this) – A list of required inventory. – Maintenance and service requirements	Input: Weekly plan Output: Task list for upcoming shift	Monitoring and resetting rates are often most successful using a FMS. The frequency of data updates will significantly impact how this process is supported Future, more mature SIC systems may see this process driven by advanced AI and/or machine learning solutions

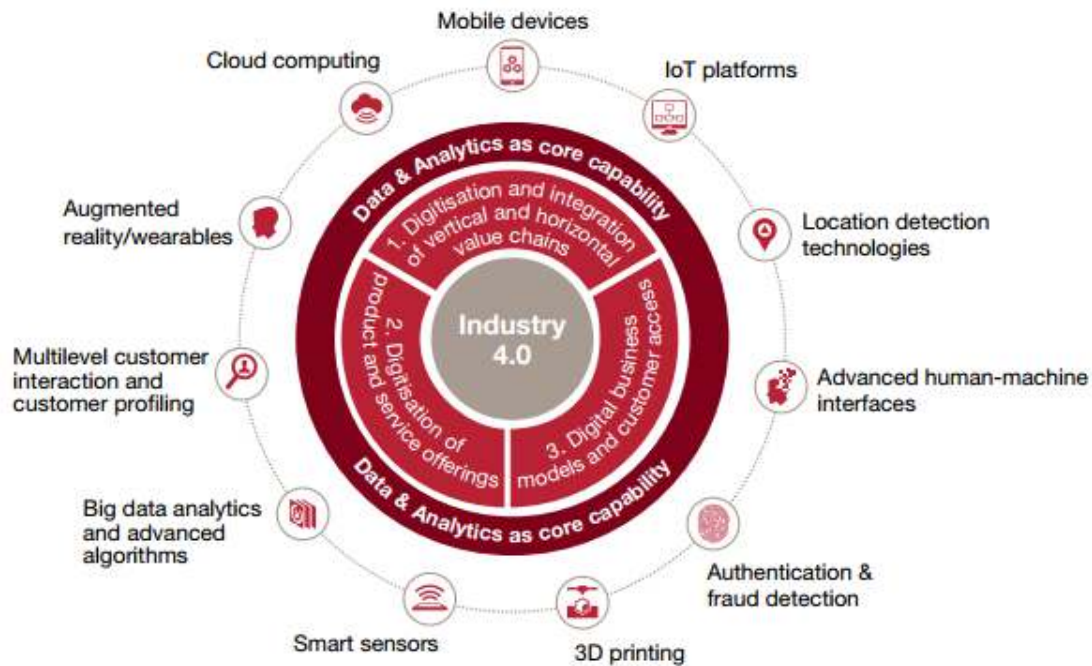
Source: GMG Group (2019)

The following section discusses aspects related to mobile technology.

### 2.9.2 Mobile technology

Mobile technology has been a subject of TTF theory research for some time (Gebauer, Shaw & Gribbins, 2010; Gebauer & Shaw, 2004; Swanson & Bellanca, 2018). This present study explored mobile technology (mobile hardware devices – iPad and iPhone) for SIC implementation. The SIC system under study was composed of mobile applications (apps), such as groundHog (fleet management system), Deswik Ops (scheduling), Outlook application (email communication), and Cisco Webex application (communication and collaboration).

The increased use of new technology to change the existing business models and the bottom line is known as the 4th Industrial Revolution (IR 4.0) (WEF, 2017). The Fourth Industrial Revolution (IR 4.0) is also referred to as Industry 4.0. This has an impact on the technology roadmap frameworks. Figure 2.12 shows that mobile technology is part of Industry 4.0 framework (PricewaterhouseCoopers [PwC], 2016).



**Figure 2.12: Framework of Industry 4.0 Technologies**

Source:PwC (2016)

Industry 4.0 is defined as an "overarching concept describing an ongoing industrial revolution triggered by a new wave of technological innovation," according to Culot et al. (2020). 'Digital transformation', 'smart manufacturing', and the 'fourth industrial revolution' are words used to characterise Industry 4.0. (Culot et al.,2020). According to Nascimento et al. (2019), advancements in information and communication technologies, as well as data storage, have resulted in technologies such as the Internet of Things (IoT), augmented reality, additive manufacturing, big data, cloud computing, simulation, industrial automation, and cybersecurity. Other additional technologies that are part of Industry 4.0 as explained by Culot et al. (2020) include vertical and horizontal system integration, advanced robotics, and – most recently – the blockchain technology.

Industry 4.0 technologies are recognised for enhancing efficiency, improving product customisation, delivering value-added services to customers, and creating social changes in the workplace through new forms of communication and entertainment (Nascimento et al., 2019). Many companies and areas of society are beginning to recognise the importance of Industry

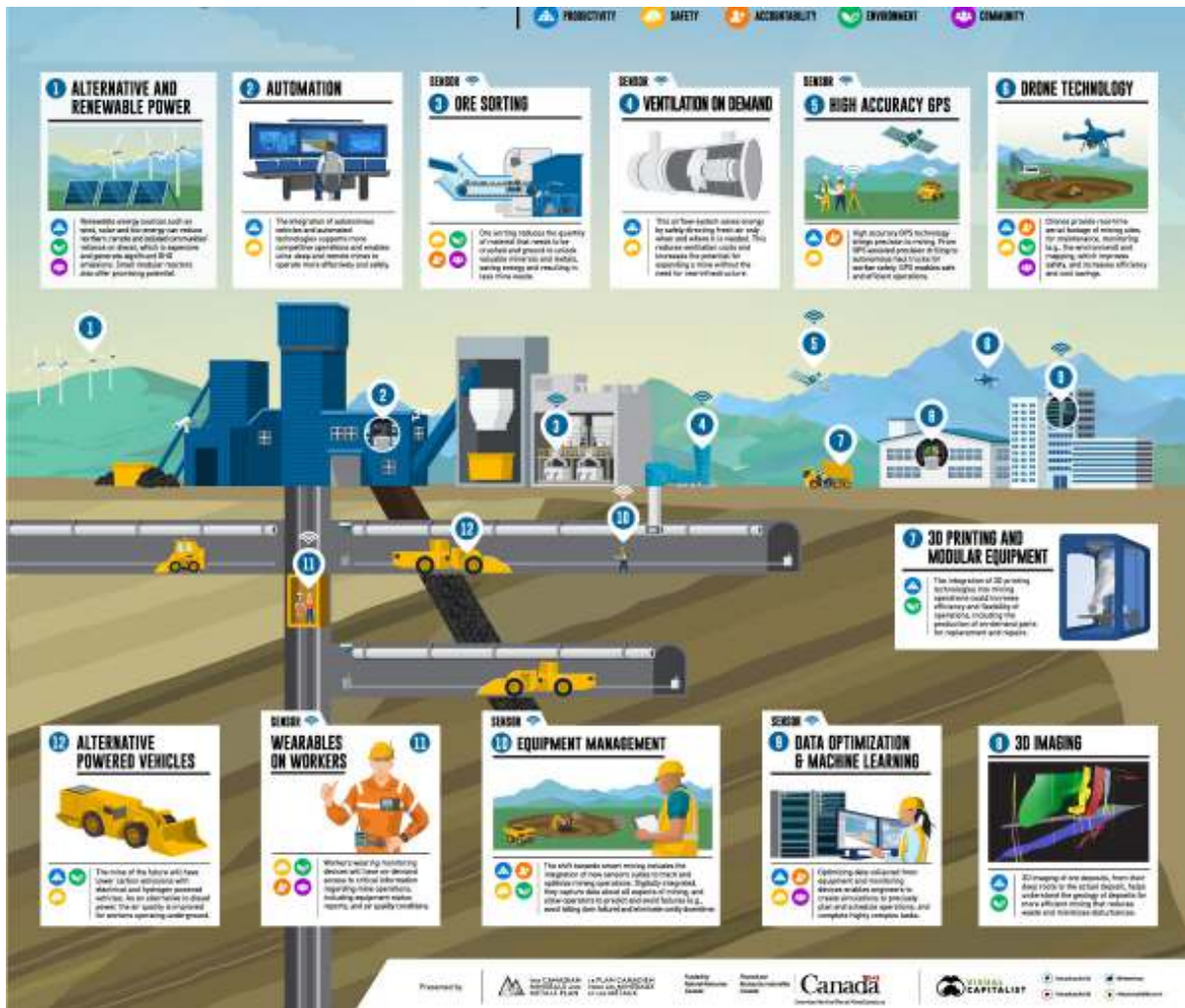
4.0 technologies (Culot et al., 2020). The use of these technologies has not been spared in the manufacturing and mining industries. For example, there is a push to transition from the concept of a digital factory to a smart factory, which merges physical and cyber technology while incorporating various Industry 4.0 technologies into the manufacturing process (Chen et al., 2018). When manufacturing data is analysed, the smart factory can achieve dynamic re-configuration and production optimisation, allowing it to respond to changes in the business model (Chen et al., 2018). Industry 4.0, according to Culot et al. (2020), has numerous effects on manufacturing configuration, including "(1) new value offering, (2) location decisions, (3) governance of activities, and (4) size of manufacturing companies".

Similarly, there is a drive for the concept of a smart mine in mining, which is closely tied to manufacturing and adopts a lot of technology and procedures from manufacturing. A smart mine, according to Xu et al. (2019), is an "unmanned mine that actively senses, automatically analyzes, and quickly processes towards the production, occupational health and safety, and technology". They said that the goal of a smart mine is to promote continuous development, and that smart mines are safe, efficient, and clean mines. Furthermore, according to Xu et al. (2019),

*"Smart Mine is based on the research of mechanical mine and automated mine, awareness-based mining research on coal mining enterprises through integrated automation, information management and engineering digital of mastery, combined with Internet , artificial smart, big data , virtual simulation, visualization, spatial information technology, network integration and cloud technology, 3D simulation and virtual reality and other advanced information technologies in an efficient, safe, green mining as the goal, the construction of highly smart, automated, user-friendly smart of mine".*

Mining is slowly extensively making use of Industry 4.0 technologies. Xu et al. (2019) proposed a three-stage method to its development, beginning with smart working and driving faces (1.0 era), progressing to smart mining technology (2.0 era), and eventually to smart mining technology (4.0 era) (3.0 era). For example, Zhao (2020) claims that integrating industry 4.0 technologies such as the IoT into the smart mine will result in a faster grasp of the catastrophe situation and more rational decision-making and communication to workers underground for evacuation. Further, the technologies have the potential to improve the underground safe-haven system by understanding the underground employees' working

environment at all times and providing adequate rescue conditions for workers above ground. Figure 2.13 shows one of the proposed smart mines (LePan, 2019).



**Figure 2.13: Smart mine**

Source: (LePan, 2019)

The concept and execution of smart mines or smart factories are still in their early phases. Because of the rapid advancement of equipment manufacturing, Chen et al. (2018) emphasised that smart factories must be adaptable and trustworthy, as well as meet high quality standards, presenting chances for intelligent manufacturing implementation. However, there are still some issues and challenges, such as the need to improve the intelligence level of manufacturing equipment, the lack of standards for the Industrial Internet of Things (IIoT) that allow for deep integration of information and industrialisation, and the lack of use of manufacturing data (knowledge-driven manufacturing) due to high dimension, variable metric, and high noise (Chen et al., 2018). The

issues and challenges that exist in the smart factory also exist in smart mines. Zhao (2020), for example, claimed that the deployment of IoT technologies in smart mining environments is hindered by a lack of standards, ubiquitous sensor networks, application-level information fusion, and multi-disciplinary, multi-professional platforms for collaborative work. According to Xu et al. (2019), the level of automation and smart technology in coal mines is still low, mining equipment dependability must be improved, and visualisation technology in hostile environments must be resolved. In order to achieve smart unmanned mining, more technology that simulates human sensory and brain activities is required.

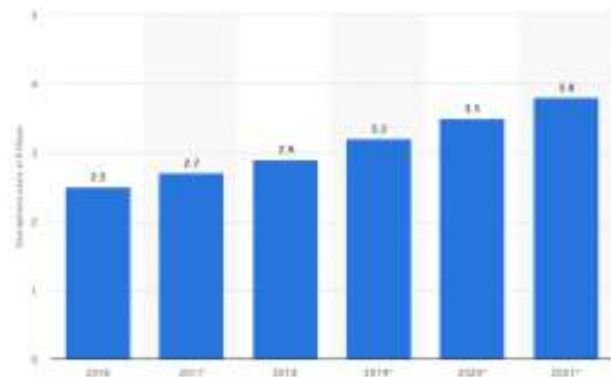
Industry 4.0 technologies are clearly playing an increasingly important role in the design and implementation of smart mines. Despite the difficulties in developing smart mines or smart factories, there is a lot of advanced research and development going on to ensure that these smart mines can become the mines of the future. Even though the number of smart mining technologies is still low, Xu et al (2019) discuss that some smart mining technology in smart perception, independent decision-making, and other smart-level technologies is still being developed. Sensors that support monitoring and collecting of relevant data in the manufacturing process, as stated by Xu et al. (2019), are another form of technology that has made significant progress. To improve, further research is being conducted that will result in improved "accuracy, transmission speed, data collection amount, anti-interference ability, seismic resistance, waterproof, dust penetration and stability", according to Xu et al. (2019).

It is clear that mobile technologies are an important aspect of the smart mine concept. Mobile technology adoption, use, and integration with mining duties are vital for smart mine development. The use of mobile phones has escalated across various sections of society, which has resulted in more business opportunities. A study by Statista (2020) reported that the world would have 3.8 billion smartphone users by 2021. It also estimated that smartphones with Android operating systems would occupy a significant market share of 85.9%, and followed by Samsung at 21.6%. The sales of smartphones worldwide were estimated to reach 522 billion dollars (Statista, 2020). Figure 2.13 illustrates the trend of global smartphone users in billion.

Mobile apps have been linked with architecture elements, including an increment in 5G wireless service, the advent of artificial intelligence and the Internet of things, better mobile application security, rise in use of bots, predictive analytics, and blockchain. As a result, business models rely on mobile technology for higher reliability and better benefit realisation (Kalkandha, 2020).

Kalkandha (2020) listed the advantages of using mobile apps for businesses of all sizes. First, mobile apps offer a type of availability where the businesses relate to the consumers, provide consistent service, and allow consumers to buy products at any time. The use of bots to connect with the consumers has improved business – customer interactions. Second, some features, such as push notifications, remind consumers about services and products that allow for a robust and direct marketing channel, thus enabling direct communication with consumers. Through the mobile app, users have access to all information to make purchasing decisions. Third, mobile apps provide prioritised value to consumers via loyalty programmes, such as rewarding subscribers. Next, the mobile apps enable building brand and recognition, such as billboard sign features and consumer involvement in product development based on their feedback and engagement in beta testing programs. Moving on, consumer engagement increases as more people use mobile phones to communicate. The mobile apps provide a unique approach that enables an organisation to stand out from its rivals as it offers competitive advantage. The resulting market and product intelligence information enables a company to grab better market share. Last but not least refers to the consequent building of customer loyalty by remaining closer to customers constantly with just a 'fingertip' away.

Improvement in mobile technology architecture and better integration with other IR 4.0 technologies have been attractive value propositions to many industries. Mobile apps and other architecture elements have caused business models to rely on reliable mobile technology (Kalkandha, 2020).



**Figure 2.14: Number of smartphone users globally**

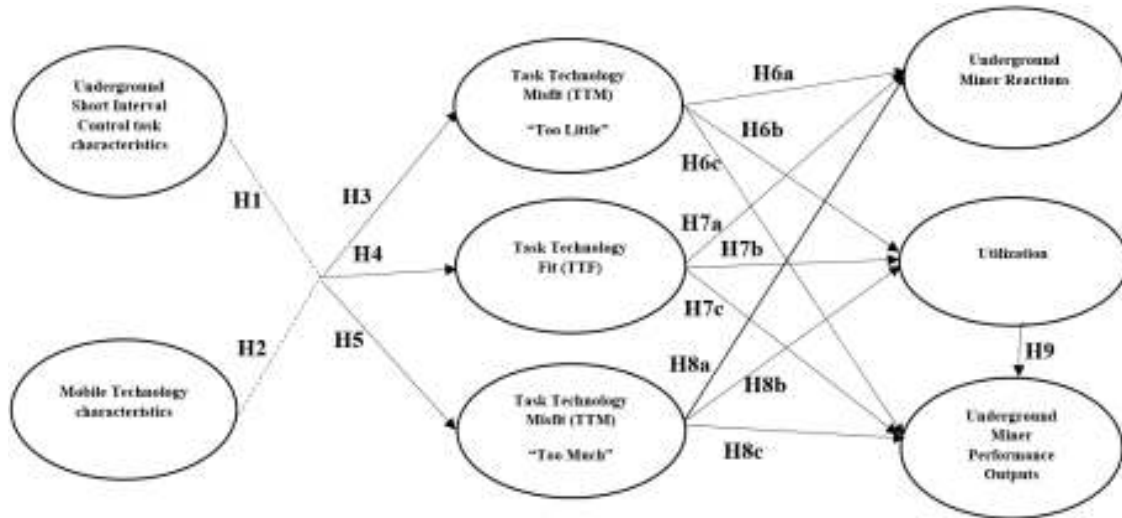
Source: Statista (2020)

## 2.10 Research model and hypotheses development

The model and hypotheses are discussed in the next sections.

### 2.10.1 Research model

The research model (Figure 2.15) in this study was inspired by prior research in TTF. The study followed the foundation theoretical framework by Goodhue and Thompson (1995) and the more recent TTF/M Theoretical framework by Howard and Rose (2019). While the initial framework by Goodhue and Thompson (1995) was more focused on TTF, Howard and Rose (2019) included the concept of TTM and user reaction resulting in the refined TTF/M model. The present study used the Howard and Rose (2019) model in the context of underground gold mining and specifically looking at underground miners using mobile technology for the SIC business process. The research model was divided into several components. First, the formal hypotheses revolved around the effects of SIC characteristics and mobile technology characteristics on TTM – “Too Little”, TTF, and TTM – “Too Much”. In the second stage, the potential relationships among TTM (Too Little/Much), TTF, user reaction, utilisation, and performance outcomes were assessed. This study empirically tested the proposed hypotheses. The next section discusses the research model rationale and justification of the hypotheses.



**Figure 2.15: The research model**

Source: Adapted from New Visual Representation of TTF Theory by Howard and Rose (2019)

## **2.10.2 Hypotheses**

### ***2.10.2.1 The impact of underground short interval control task characteristics on TTF/M***

As explained earlier, Goodhue (1995) defined tasks as actions performed to turn inputs into outputs. The GMG Group (2019) discussed critical SIC tasks as planning, situation awareness, resource management, and operational decision making. The application of SIC tasks in mining has existed for some time. Visser (2020) proposed the alignment of management practices, which includes optimisation of SIC. Visser (2020) added that such adjustment should take advantage of the increased availability of information and data analysis capabilities by using real-time measurements and artificial intelligence. The understanding of the role of these tasks in achieving task technology fit/misfit is key. The outcomes would be agile enough to quickly respond to changes in conditions and provide accurate and timely information to decision-makers, thus resulting in opportunities to enhance performance at mining operations. The following were hypothesised in this study:

*H1a: Underground short interval control task characteristics positively influence TTM - “Too Little”.*

*H1b: Underground short interval control task characteristics positively influence task-technology fit (TTF).*

*H1c: Underground short interval control task characteristics positively influence TTM - “Too Much”.*

### ***2.10.2.2 The impact of mobile technology characteristics on TTF/M***

Goodhue (1995) defined technology as one’s tool to execute tasks. Gebauer and Tang (2008) discussed how mobile technology focused on user mobility would achieve TTF. They found that the mobile devices’ relationship between task difficulty and the functional requirement was stronger in high mobile device users than less mobile device users. They concluded that user mobility should be considered upon applying TTF for mobile IS. Essentially, mobile devices have numerous other benefits aside from user mobility. These can still apply to the mining industry, where mobile technology is applicable for SIC. Staples and Seddon (2004) found that TPC user evaluation relied on mandatory versus voluntary technology use. Gebauer et al. (2010) depicted that while mobile IS hold great promise in supporting organisational processes (e.g. SIC), fewer guidelines exist on designing effective mobile IS. Thus,

understanding how mobile technology characteristics such as connectivity, collaboration, communication, portability, real-time etc. (Shehzad & Rozan, 2018; Gebauer et al., 2010) would help in knowing how to manage TTF/M. The following were hypothesised in this study:

*H2a: Mobile technology characteristics positively influence task-technology misfit with “Too Little”.*

*H2b: Mobile technology characteristics positively influence task-technology fit.*

*H2c: Mobile technology characteristics positively influence task-technology misfit with “Too Much”.*

### ***2.10.2.3 The impact of the interactive effect of underground short interval control tasks and mobile technology characteristics on TTF/M***

Drazin and De Ven (1985) explained that structural contingency theories are congruent theories upon claiming that organisational context is related to its structure. Their empirical study tested the three approaches to fit: selection, interaction, and systems approaches. They asserted that the three forms of fit were not mutually exclusive. The study by Drazin and De Ven (1985) focused on the task-contingency theory of work design and examined this within the context of the three forms of fit. They concluded that managerial selection had a significant impact on structural characteristics and a substantial correlation among setting, structure, and process. The study by Drazin and De Ven (1985) discussed an interaction approach to fit. Howard and Rose (2019) explained the important role of the interactive effect of the task and mobile characteristics in achieving TTM/F. Thus, the following were proposed in this study:

*H3: The interactions of underground SIC task characteristics and mobile technology characteristic pairs positively influence TTM – “Too Little”.*

*H4: The interactions of underground SIC task characteristics and mobile technology characteristic pairs positively influence TTF.*

*H5: The interactions of underground SIC task characteristics and mobile technology characteristic pairs positively influence TTM – “Too Much”.*

#### ***2.10.2.4 The impact of TTF/M on underground miner reaction, utilisation and performance outcomes***

The concept of 'fit' has been widely cited in TTF studies (Howard & Rose, 2019). Goodhue and Thompson (1995) argued that TTF focuses on the degree to which system characteristics match user task needs, in which higher TTF results in better performance. The TTF can also be defined as the extent to which technology functionality matches task requirements and individual abilities. They argued that TTF generates higher performance if users apply technology to perform the task.

As earlier discussed, in refining and extending the Goodhue and Thompson (1995) TTF theoretical framework, Howard and Rose (2019) initiated the concept of TTM divided into 'Too Much' and 'Too Little'. TTM – 'Too Much' referred to a type of misfit between the technology and tasks due to either the technology or the tasks having too many features while TTM – 'Too Little' referred to a type of misfit between the technology and tasks due to either the technology or tasks fit features being too little.

Vessey (1991) discussed the importance of aligning the representation of a problem and the tasks that should be performed to address it.

The mining industry is relatively new to the use of digital technology (GMG, 2019). For this reason, it is important to take into consideration the reactions of underground miners to the TTF/M. User reactions are defined by Bhattacharjee et al. (2008) as users' views and general dispositions towards a specific IT system and its "impact on their job within its socio-historical context". According to Moore and Benbasat (1991), perceptions play a key influence in determining whether or not a person will adopt an information technology (IT) innovation. Understanding such emotions is crucial because they often reveal future user behavior in terms of IT use "(i.e., whether they will accept or oppose it, or whether they would be receptive or resistant)" (Bhattacharjee et al, 2008). According to Howard and Rose (2019), Moore and Benbasat (1991) discussed that relative advantage and ease of use scales are useful for this construct. Thus, the following hypotheses were proposed in this study:

*H6a: TTM – "Too Little" will positively influence underground miner reactions.*

*H6b: TTM – "Too Little" will positively influence utilisation.*

*H6c: TTM – "Too Little" positively influences underground miner performance outcomes.*

*H7a: TTF positively influences underground miner reactions.*

*H7b: TTF positively influences utilisation.*

*H7c: TTF positively influences underground miner performance outcomes.*

*H8a: TTM – “Too Much” positively influences underground miner reactions.*

*H8b: TTM – “Too Much” positively influences utilisation.*

*H8c: TTM – “Too Much” positively influences underground miner performance outcomes.*

#### ***2.10.2.7 The impact of TTF/M on performance outcomes mediated by utilisation***

Goodhue and Thompson (1995) discussed performance as subject to using technology. As a construct in the TTF model, performance output has been broadly discussed in the literature, with Venkatesh et al. (2003 cited in Zhou, Lu & Wang, 2010) relating it to perceived usefulness that reflects performance improvement brought about by technology. This present study applied this background and revisited the work by Goodhue and Thompson (1995) and Howard and Rose (2019). These researchers explained that individual performance impacts TTF that develops total dependence on technology. In this study, the underground miner refers to anyone who works at an underground mine executing different tasks related to mining. Thus, the following were proposed in this study:

*H9a: TTM – “Too Little” mediated by utilisation positively influences underground miner performance outcomes.*

*H9b: TTM – “Too Much” mediated by utilisation positively influences underground miner performance outcomes.*

*H9c: TTF mediated by utilisation positively influences underground miner performance outcomes.*

#### ***2.10.2.7 The impact of utilisation on performance outcomes***

Goodhue and Thompson (1995) defined utilisation as the extent to which the information system is integrated into the individual work routine, regardless of individual choice or organisational mandate. In this present study, the use of SIC mobile technology systems was mandatory as part of the organisation policy, as prescribed by Goodhue and Thompson (1995). Thus, the following were proposed in this study:

*H9d: Utilisation positively influences underground miner performance outcomes.*

## **2.11 Chapter conclusion**

Goodhue (1995) made a significant contribution to the impact of IS on performance by providing a theoretical sound construct to user evaluation. As previously discussed, the effects of technology on user evaluation can be categorised into two streams: utilisation and TTF, with each stream having several advantages and disadvantages (Goodhue & Thompson, 1995). Goodhue and Thompson (1995) proposed a novel TPC or better known as TTF theory that brought the two research streams together.

The Task-Technology Model has continuously gained research interest, resulting in developments that address IS theory and practice concerns. As a user evaluation construct, the proposed TTF formed a theoretical basis for evaluations (Goodhue, 1995). The combination of the two research streams, utilisation and TTF, generated the TPC (Goodhue & Thompson, 1995). The TPC (or TTF theory) has enabled further TTF theory applications in many industries and contexts (Spies et al., 2020), with many researchers applying and extending the TTF theory. Many researchers have also agreed that the TTF is not perfect as it still needs further refinement and extension (Howard & Rose, 2019; Spies et al., 2020). This present study was built on the work by Howard and Rose (2019), who extended and refined the TTF by operationalising it, introduced TTM, and used interactive effects over direct effects measurements.

This chapter has presented the reviewed seminal articles on TTF by providing a historical perspective of the theory and discussing the improvements that have been made to it over the years. The chapter described the SIC as the framework of analysis for tasks, mobile technology, and the associated fit constructs applied in this present study. Next, this chapter outlined the hypotheses and the research model. Although many questions or concerns exist within the TTF theory research field, this present study uses the newly proposed TTF and TTM models by Howard & Rose (2019) and applies it to the context of underground mining.

## **CHAPTER 3: A CASE STUDY OF DIGITAL SIC AT TURQUOISE RIDGE UNDERGROUND DIVISION**

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### **3.1 Introduction**

This chapter presents the case study of the Turquoise Ridge underground division. It delves into the geographical setting, history, current, and production figures of the studied mine. The general operating workflow of the underground mine and the driving need for operational excellence are discussed in this chapter. The digital transformation programme, particularly mobile technology implementation and short interval control (SIC) tasks and their impact on the underground workflow process, is delineated.

### **3.2 Turquoise Ridge underground mine**

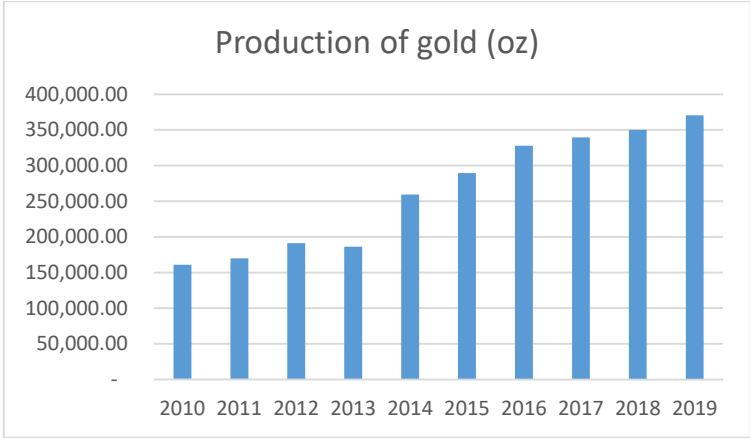
The Turquoise Ridge Complex, located in Humboldt County, Nevada, USA, comprises Turquoise Ridge underground, Vista Underground, and Turquoise Ridge Surface (Mega and Visa Open pits) (Nevada Gold Mines, 2020). The vast area has been operated by the Nevada Gold Mines (2020), which reported that copper, silver, and lead mining activities have been carried out at Turquoise Ridge Underground since 1883. Interestingly, gold was discovered at the present-day Getchell mine site in 1933, which generated 788,875 ounces of gold in total from 1934 to 1945. The production of gold at Getchell mine was, however, inconsistent between 1960 and 2009. An in-depth drilling programme deployed in 1993 with advanced planning and engineering resulted in a new underground mine completed by 1995. According to the Nevada Gold Mines (2020), activities at the Getchell Main underground mine were suspended in 2000. Despite commencing production in 2003, the mine was placed under care and maintenance in 2008 due to several operational and safety issues (Nevada Gold Mines, 2020). Figure 3.1 illustrates the Turquoise Ridge Mine located in Nevada, USA).



**Figure 3.1: Location of Turquoise Ridge**

Source: Nevada Gold Mines (2020)

Chart 3.1 presents the production of gold for 2010-2019 at the Turquoise Ridge underground mine.



**Chart 3.1: Turquoise underground gold production (2010-2019)**

Source: Adapted from Nevada Gold Mines (2020)

### **3.3 Geology and mineralisation**

The Turquoise Ridge underground houses mineral reserves accumulating up to 28 million tonnes of 11.01 g/t gold (Nevada Gold Mines, 2020). To be precise, “the Turquoise Ridge deposit is a typical Carlin-type deposit, which is characterised by structurally and stratigraphically controlled, sediment-hosted, replacement deposits containing disseminated micron-sized gold. The gold occurs in arsenic-rich rims that form on pyrite” (Nevada Gold Mines, 2020).

### **3.4 Turquoise Ridge underground mining methods**

According to Nevada Gold Mines (2020), refractory (carbonaceous/sulphide) gold ore with high grade is yielded in the Turquoise Ridge underground. Accessibility of the underground operation is enabled by dual shafts and a system composed of internal ramps. Several mining techniques are applied at the mine, including sill benching, mechanical mining, as well as underhand drift, and cemented rock fill.

### **3.5 Third Shaft Project**

The Third Shaft Project undertaken at the Turquoise Ridge underground, as described by Nevada Gold Mines (2020), denotes “sinking and equipping a 7.3 m diameter, concrete-lined shaft to 990 m total depth with shaft infrastructure of two skipping levels and a shaft bottom pump level”. As outlined by Nevada Gold Mines (2020), one of the benefits offered by the new shaft is its function as a second production shaft. To further describe this, Nevada Gold Mines (2020) explains that the new shaft provides “higher hoisting and ventilation capacities, as well as shorter hauls underground at the North Zone, besides paving a secondary escape path at the north end of the mine”.

According to Nevada Gold Mines (2020), the site preparation for the Third Shaft commenced in 2017. The major milestone of shaft sinking began in 2017, with its final commissioning targeted in late 2022.

### **3.6 Mining challenges and opportunities**

Reclamation and closure work and legacy/historical activities are ongoing at the site (Nevada Gold Mines, 2020). The activities include access and haul roadways, infiltration, water treatment plant, wastewater treatment, and potable water systems and tailings impoundment

work. The report added that the listed elements and aspects will be reclaimed and halted from any operation at the end of mine life.

As reported by the Nevada Gold Mines (2020), since gold production at the Turquoise Ridge underground mine division has been increasing over the years, there is a chance to further optimise the mine by probing into several essential dependent factors, as depicted in the following:

*“operating costs reduction, optimisation of mechanical mining techniques to enhance mine throughput, optimisation of Turquoise Ridge Underground to completely capitalise on the synergies derived from the merger with Newmont, provision of adequate stoping areas, transition to undercut stoping from top cut development, and optimum yield after infrastructure completion of the Third Shaft project that minimises haulage demands at the North Zone” (Nevada Gold Mines, 2020).*

### **3.7 Digital transformation in mining**

Apparently, numerous mining companies face similar challenges experienced by the Turquoise Ridge underground division, including licence to operate, deepening ore bodies, environmental and safety aspects, increment in fuel costing, and lower capital investment (WEF, 2017). Despite the strong support offered by local and other business associates (Great Western Mining, 2020), Nevada mining has been affected by the significantly changing environment that demands more time for operation accessibility (Nevada Gold Mines, 2020). Notably, the progress of this industry relies heavily on management style, metal price, costs, licence for operation, production, and ore body. The industry can be greatly affected if any variable faces a threat. For instance, an environmental issue that involved Vale – a world-leading iron ore mining conglomerate in Brazil – witnessed the collapse of tailing dams. The catastrophic event caused more than 65 deaths and a share drop in price by 20%. As a result, the Brazilian government pursued criminal charges against the executives. If any collusion with safety auditors of the mining tailings dams was found, the company would be fined \$7 billion (Pearson & Lewis, 2021). The slump in metal price led to a reduction in the bottom line for numerous mining companies. Recent research work reported escalating capital as ore bodies are getting deeper for accessibility. As a result, a range of strategies has been proposed by multiple quarters to make the mining industry one that is sustainable, durable, socially acceptable, and profitable through the deployment of digital transformation (Ditton & Beer, 2018).

### **3.8 Digital short interval control at Turquoise Ridge**

Among the many digital transformation initiatives implemented at the Turquoise Ridge underground mine division is that which refers to the digital SIC. The National Mining Association (NMA, 2018) described the operation of an underground SIC system, as explained by Barrick, the operator of Nevada Gold Mines who owns Turquoise Ridge, underground mine division. The objectives of SIC include providing visibility of underground mining activities to enable supervisors and operators to have near real-time operational information as mining progresses. This identifies which mining process areas can generate higher production in a safe and environmentally acceptable manner.

Many underground mines have applied paper-based SIC for many years. The SIC system is crucial for asset optimisation and personnel utilisation. Organisations that deploy digital platforms to record data digitally and drive quick decision-making at varying management layers result in a clear assessment of achieving and planning goals (Savit et al., 2018).

The SIC process at Turquoise Ridge incorporated a mobile platform with three mobile applications: a fleet management technology called groundhog, a collaboration platform called Cisco Webex teams, and an analytic platform called Microsoft Power BI. These three applications were presented to the end-user as mobile applications and were run using iPads.

The Barrick digital underground SIC employed at the Turquoise Ridge underground division applied the typical SIC cycle depicted in Chapter 2, where scheduling is performed initially based on weekly and short-term plans. This is coordinated by the engineering team working closely with the mining operations centre. Both operators and equipment are assigned as per scheduled tasks, and this is well discussed with the operator and super input during the line out or shift start meeting. The operators move to their assigned equipment, where they perform shift start equipment inspections and log the information in the fleet management system, which works off mobile devices. The underground operators can detect their equipment in the system and enter login credentials as they start their shift. During the shift, each team member can communicate with the other team members using Cisco Webex Meetings. The control centre can monitor where the equipment and underground operators are using the Mobilaris system, thus providing real or near real-time information on the location of personnel and equipment and the groundhog fleet management system and its work status. The underground operators or miners can punch their work progress on the mobile groundhog application on their mobile devices, thus enabling the information to be available to supervisors and the mine

operations centre in real or near real-time. While the shift progresses based on the information, the work plan may change. This is updated in the core system and automatically appears on an underground operator or miner mobile device. This is also communicated via Cisco Webex meeting channels that allow the operators to ask questions and perform two-way communication. This instant update and communication of workplace changes using mobile technology enable effective communication by supervisors and operators to adapt the shift plan to any changing circumstance. Figure 3.2 illustrates the operation of the Barrick underground SIC.



**Figure 3.2: Barrick underground short interval control**

Source: NMA (2018)

### 3.9 Chapter conclusion

This chapter presented an overview of the Turquoise Ridge case study by describing the mine's historical and geographic set up. The challenges experienced by the Turquoise Ridge division include licence to operate, deepening ore bodies, environment and safety, increased fuel costs, and lower capital investment (WEF, 2017). Hence, the adoption of digital transformation as a strategy to overcome the listed obstacles is in line with the reported objectives of the operator, Barrick (2019). The setting presents a great opportunity to explore the implemented SIC system further.

### 4.1 Introduction

This chapter begins by revisiting the research question and objectives. A hypothetical-deductive research design was adopted in this study. The chapter presents the unit of analysis used for this study. The research design using the onion model proposed by Saunders, Lewis and Thornhill (2009, pp. 20–136) is also discussed. The epistemological posture is discussed in light of the study goals. After describing the research strategy and methodology, the research horizon is outlined. The chapter also discusses the development of data collection tools and data analysis procedures, the reliability and validity of this study, as well as the ethics that applied while conducting the study.

### 4.2 Research questions and hypotheses

This section restates the research question that drove this study, as given in the following:

*What are the implications of short interval control tasks fit and misfit with mobile technology applications used by operational level miners in an underground gold mine?*

Using the refined Task-Technology Fit framework proposed by Howard and Rose (2019) and contextualising its application to the case of SIC process implementation using mobile technology in underground mining, the variables were identified from the primary constructs, namely SIC tasks, mobile technology, TTM (Too Little/Much), TTF, utilisation, user experience, and performance. These resulted in the development of the research model, as discussed in the previous chapter.

### 4.3 Unit of analysis

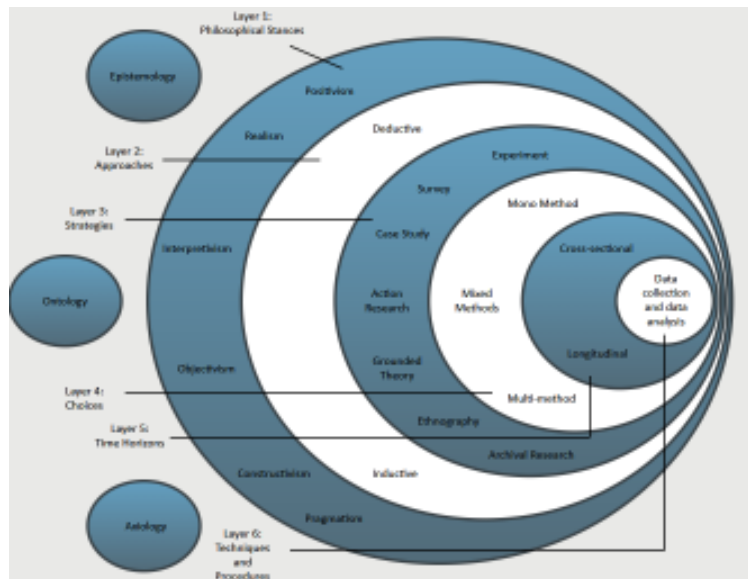
This study on TTF focused on individual underground miners as the study target. The unit of analysis refers to individual underground miners who adopted the mobile technology enabled SIC system for TTF/TTM. Bhattacharjee (2012) asserted that good understanding of the unit of analysis results in clear identification of the type of data a researcher will collect and who they will collect the data from. By specifying the unit of analysis as underground miners, this present study distinguished the type of TTF being used. This important as there is task technology theory that applies to groups as well (Zigurs & Buckland, 1998). As discussed

earlier, this study used the refined TTF model proposed by Howard and Rose (2019), based on the original framework initiated by Goodhue and Thompson (1995), which focused on individuals and not groups.

#### 4.4 Research design

Research design denotes a high-level plan that guides the response of a researcher to the research question(s) (Saunders et al., 2019, pp. 20–136). Although the process of crafting a research design differs among researchers due to the nature of research, experience, and beliefs, Saunders et al. (2019) claimed that a good research design maintains clear objectives while specifying the related research philosophy, research strategy, methodology, data collection tools, and data analyses approaches.

The research onion proposed by Saunders et al. (2019) was adopted in this study as a guide to developing a robust research design suitable for the study. Figure 4.1 illustrates the research onion.



**Figure 4.1: Research onion**

Source: Saunders et al. (2009, pp. 20–136)

##### 4.4.1 Research philosophy

Saunders et al. (2019) defined research philosophy as a "system of beliefs and assumptions about the development of knowledge". The underlying need for this study is to contribute empirically to the body of theoretical and practical knowledge. Hence, a rigorous scientific

standard was adopted for this study. The researcher's beliefs and assumptions in the theory of knowledge are crucial as they influence the selection of the epistemological posture which is appropriate for the research.

Girod-Séville and Perret (2001) defined epistemology as “the study of knowledge, and so of science: the study of its nature, its validity and value, its methods and its scope”. They explained that epistemology is a significant component of any research and enables researchers to have validity and legitimacy.

In selecting the appropriate epistemology, the researcher used a research design approach as illustrated in Figure 4.1. Girod-Séville and Perret (2001) explain that “all research work is based on a certain vision of the world, employs a methodology, and proposes results aimed at predicting, prescribing, understanding, or explaining. By recognizing these epistemological presuppositions, researchers can control their research approach, increase the validity of their results and ensure that the knowledge they produce is cumulative”.

The recognition of the vision of the world is the fundamental step of any research process (Girod-Séville & Perret, 2001; Saunders et al., 2019). Girod-Séville and Perret (2001) suggested starting by looking at the significant paradigms representing the main epistemological streams of organisation science. This approach is also evident in the research onion proposed by Saunders et al. (2019). Girod-Séville and Perret (2001) quoted Kuhn (1970) who explained that paradigms are models, intellectual frameworks of frame of reference with which researchers in organisation science affiliate themselves. Girod-Séville and Perret (2001) explained that these epistemological positions are positivist, interpretivist, and constructivist paradigms. Saunders et al. (2019) have additional classifications, and these are on a continuum from positivism, critical, realism, interpretivism, postmodernism, to pragmatism. Table 4.1 shows the major epistemological positions discussed by Girod-Séville and Perret (2001). The researcher used these paradigms to position themselves based on their beliefs and specific research under study.

**Table 4.1: Epistemological positions**

Epistemological questions	Paradigms		
	Positivism	Interpretativism	Constructivism
Status of knowledge	<b>Ontological hypothesis:</b> The knowledge object has its own essence	<b>Phenomenological hypothesis:</b> The essence of the object is multiple (interpretativism), cannot be attained (moderate constructivism) or does not exist (radical constructivism)	
	Independence of subject and object	Dependence of subject and object	
Nature of 'reality'	<b>Determinist hypothesis:</b> The world is made up of necessities	<b>Intentionalist hypothesis</b> The world is made up of possibilities	
How is knowledge generated?	<b>Discovery</b>  The research question is formulated in terms of 'for what reasons ...'	<b>Interpretation</b>  The research question is formulated in terms of 'what motivates actors to ...'	<b>Construction</b>  The research question is formulated in terms of 'to what ends does ...'
	Privileged status of explanation	Privileged status of understanding	Privileged status of construction
What is the value of knowledge? (Validity criteria)	Degree of confirmation Refutability Logical consistency	Credibility Transferability Dependability Confirmability	Adequacy 'Teachability'

Source: Girod-Séville and Perret (2001)

The researcher comes from a nature science background. The belief systems, namely the status of knowledge, nature of knowledge, how to generate knowledge, and value of knowledge, especially within the study context, resulted in the researcher selecting a positivism paradigm. Saunders et al. (2019) explained that the “positivism relates to a philosophical stance of the natural scientist and results in working with observable social reality to produce law-like generalizations”. Positivism is believed to have originated from the works of Francis Bacon, Auguste Comte and the early 20<sup>th</sup> century group of philosophers and scientists called the Vienna circle. Saunders et al. (2019) discussed that the word positivism refers to what is “posited”– i.e. “given” and that it is focused on the scientific empiricist method designed to yield pure data and facts uninfluenced by human interpretations or bias.

Many researchers agree that positivism views reality as existing, external, independent of the subject, thus observing it as objective truth or one true reality (universalism) and thus knowledge produced by positivism's objective and relates to revising and applying existing laws (Girod-Séville & Perret, 2001; Saunders et al., 2019).

In the case of the present research, this can be interpreted as follows: by adopting the positivism paradigm as an epistemological position, the researcher examined the short interval control process which is dependent on the technical or organisation reality of mining operations at Turquoise Ridge underground division in Nevada, USA.

As explained above, the research design which resulted in the use of the positivist paradigm was appropriate for the study design. The resulting use of the existing TTF theory and testing the hypotheses using structural equation modelling was appropriate for the study context. The hypotheses allowed for reconstruction of cause effect, both linear and multiple or circular causality. As explained by Girod-Séville and Perret (2001), the vision behind positivism of generating new knowledge is that the laws existed before they are discovered. Thus, the generation of knowledge using this paradigm still follows a path determined largely by the ideas of knowable reality and not necessarily personal beliefs.

Girod-Séville and Perret (2001) discussed that "in assessing the validity of research, positivism only recognizes as scientific those methods that respect formal logic (deductive logic)". They explained that the adoption of positivism means that 'logical consistency' needs to be followed where a demonstration is made that all propositions of a theory are related to one another by the rules of formal logic or are logically deducible from the same set of premises. Girod-Séville and Perret (2001) explained that positivism "refuses to consider inductive logic as scientific. It argues that the only logic that enables us to reproduce reality objectively is deductive logic". They explained deductive logic as one that uses true premises and the rules of formal inference to establish the truth-value of a proposition (or its non-refutation).

One of the key aspects of any knowledge creation process is validation of knowledge. This is a very important part of scientific research in general and specific in the positivism research paradigm as the validity criteria enable the researcher to distinguish between scientific and non-scientific knowledge and thus use verification, degree of confirmation, refutation and logic consistency as explained by Girod-Séville and Perret (2001).

Girod-Séville and Perret (2001) explained that empirical verification enables researchers to assess the truth of their statements. The degree of confirmation supplements verification and refers to “probabilistic logic” proposed by Carnap (1962). Girod-Séville and Perret (2001) quoted Carnap (1962) to explain that “theories are impossible to prove but they present different degrees of probability”. Another criterion for knowledge verification under the positivism paradigm is Popper’s principle of refutation, which explains that “we can never maintain that a theory is true, but we can say it is not true”. According to this principle, Girod-Séville and Perret (2001) stated that a theory is scientific if it is refutable. It is based on this principle that the research had different hypotheses to explain. Finally, the adoption of this paradigm entails that knowledge verification as explained by Girod-Séville and Perret (2001), assesses validity of research by recognising as scientific those methods that respect formal logic (deductive logic).

#### **4.4.2 Research approach for theory development**

The positivist philosophy influences theory development. The TTF theory was applied to decipher SIC and mobile technology in an underground mining phenomenon and test the hypotheses formulated for this study. The deductive approach was selected for the following reasons: (1) Instead of creating a new theory, this study employed the existing TTF theory proposed by Howard and Rose (2019) to assess the fit/misfit between SIC tasks and mobile technology (2) and the hypotheses were built based on the theory and the study context.

#### **4.4.3 Research strategy**

Saunders et al. (2019) explained that research strategy is the assessment of the research context. The selection of the most suitable research strategy is in line with the research philosophy selected by the researcher. The single case study of the Turquoise Ridge Underground mine division was selected as the research strategy. Since a case study allows for quantitative and qualitative research approaches, this study adopted the quantitative approach. Saunders et al. (2019) described a "case study as an in-depth inquiry into a topic or phenomenon within a real-life setting". This is well-aligned with using the Turquoise Ridge underground division as the research context. This underground mine division has various mining business processes, with this study concentration on the SIC business process. Chapter 3 provides a comprehensive case study of the Turquoise Ridge underground division and the mobile technology-enabled SIC business process. This study was conducted to be replicable in other contexts. The study adopted a survey design focused on the case study.

#### **4.4.4 Research time horizon**

This study denotes a 'snapshot' of the time horizon, also known as a cross-sectional study. Saunders et al. (2019) defined cross-sectional research as that which involves "studying a particular phenomenon or phenomena at a particular time". Bhattacharjee (2012) mentioned that cross-sectional studies measure both independent and dependent variables at the same time of point.

#### **4.4.5 Quantitative research approach**

The quantitative research approach was adopted in this study. This approach is well-aligned with the positivist research philosophy selected for the study. The quantitative approach is concerned with the treatment of data with high-level impartiality. The investigative technique presumes that the study data may be gathered and evaluated neutrally (Saunders et al., 2019). This approach includes numerical data, which can be primary or secondary data (Saunders et al., 2019). The quantitative approach was deemed suitable for this hypothesis-based research work as it targets to yield definitive outcomes that illustrate correlations among the variables.

#### **4.5 Population and sample selection**

This research study focused on the population of the Turquoise Ridge underground division comprised of 400 employees who have worked in four different crews. The stratified purposive sampling technique was employed to identify 200 employees with equal representation from each crew.

#### **4.6 Sources of data**

The study used primary data collected from individual underground miners via an anonymous survey, while secondary data was gathered from company publicly released information and used in developing the case study. Some of the data sources included Barrick annual reports, presentations, and SEC filings. The data was retrieved from publicly available information that described the Turquoise Ridge underground division and the SIC process. Additional mining industry white papers describing the mining method and the SIC process applied at Turquoise Ridge underground division were reviewed to gain more details for the case study.

#### **4.7 Design of data collection instrument**

A two-stage data collection exercise was executed to design a data collection instrument that could be well understood by the respondents. The first stage was a pilot data collection exercise

based on prior TTF questionnaires. The pilot survey, which was distributed using SurveyMonkey, received helpful feedback that facilitated distributing of the questionnaires to the actual respondents.

The final questionnaire was designed using the SurveyMonkey online system and sent to the sample. The questionnaire consisted of seven (7) sections. These were a demographic profile, SIC task characteristics, mobile technology characteristics, TTF and TTM, user reaction, utilisation, and individual performance. The questionnaire was adapted from previous TTF and TTM studies.

The first section had demographic questions, and the respondents were asked to answer questions regarding their gender, age group, education, mining work experience, department, system usage experience, etc. These responses to the questions helped the researcher to understand the sample.

The second section asked questions about participants' experience with short Interval control task characteristics. The researcher used the measures proposed by Goodhue and Thompson (1995) and adapted them to the context. For example, users were asked to indicate their agreement with the statement “My job requires performing the same type of tasks” on a 7 point Likert scale labelled from ‘strongly agree’ to ‘strongly disagree’.

A similar approach was followed with the third section, which focused on mobile technology characteristics, and the questions were adapted from Gebauer et al. (2010) and Shehzad and Rozan (2018), Goodhue and Thompson (1995), and adjusted to the underground mine context. As an example, users were asked to indicate their agreement with the statement “I can use the SIC mobile technology device and applications I need, regardless of where I am, i.e., Surface, Underground” on a 7-point Likert scale labelled from ‘strongly agree’ to ‘strongly disagree.’

The fourth section used a similar approach to the second and third sections. The items to measure the task technology fit and task technology misfit constructs were adapted from the previous research work (e.g. Goodhue & Thompson, 1995; and Howard & Rose, 2019). They used the three-dimensional TTF and TTM scale developed by Howard and Rose (2019).

The fifth section focused on the underground miner reaction construct and was adapted from Howard and Rose’s (2019) measures on user reactions. Howard and Rose (2019) explained that they used scales created by Moore and Benbasat (1992) to gauge user reactions. For

example, users were asked to indicate their agreement with the statement “I am passionate and enthusiastic about SIC Mobile technologies” on a 7-point Likert scale labelled from ‘strongly agree’ to ‘strongly disagree’.

The sixth construct, utilisation, was adapted from measures by Howard and Rose (2019), and it had items that gauged utilisation. For example, users had to indicate their agreement with the statement “I often use the technology to perform the task(s) at work” on a 7-point Likert scale labelled from ‘strongly agree’ to ‘strongly disagree.’

Last but not least, the construct, underground miner performance outputs, was adapted from the measure proposed by Goodhue and Thompson (1995). For example, users were asked to indicate their agreement with the statement “Using the SIC mobile technology systems, e.g. iPad, Cisco Webex, groundhog has a positive impact on my work” on a 7-point Likert scale labelled from ‘strongly agree’ to ‘strongly disagree’.

Self-reported data was gathered from underground miners who used the mobile-enabled SIC system. The questionnaire was designed by adapting the measures and scales for TTF from Goodhue and Thompson (1995), while TTM factors were adapted from Howard and Rose (2019). Table 4.2 describes the constructs and measures that were adopted to build the questionnaire for this study.

**Table 4.2: Research construct and measures**

<b>Scale</b>	<b>Items</b>	<b>Description</b>	<b>Source</b>
*SIC characteristics	Routine, non-routine, dependence, impact, participation, information qualities	Questions on characteristics of a mobile-enabled SIC system in addressing planning & scheduling, situation awareness, resource management, and operational decision making	Adapted from GMG Group (2019) Goodhue and Thompson (1995) and adjusted to the underground mine context
*Mobile technology characteristics	Connectivity, collaboration, communication, portability, real-time	Characteristics of mobile technology, e.g., mobile devices and applications	Adapted from Gebauer et al. (2010) and Shehzad and Rozan (2018) and adjusted to the underground mine context
Underground miner characteristics	Gender, employment category, age group, experience, working department, education, system use	Questions regarding the demographics and system use and competence by underground miners	Adapted from Goodhue and Thompson (1995) and adjusted to the underground mine context
*User perception	Passion and enthusiasm, positivity, IT Support	Questions focused on user reactions in using mobile-enabled SC to do their job	Adapted from Howard and Rose (2019) and Moore and Benbasat (1992), adjusted to the underground mine context
*Utilisation	Mandatory use of the system, system use as designed	Questions related to the use of the system	Adapted from Goodhue and Thompson (1995) Howard and Rose (2019) and adjusted to the underground mine context.
*Performance outcomes of miners	Dependent, intended use, quality of work, positive, faster impact, meet targets	Questions that explain the performance outcomes of miners	Adapted from Goodhue and Thompson (1995) and adjusted to the underground mine context

Scale	Items	Description	Source
*Task-technology fit/Task-technology misfit	Training and ease of use	Questions that explain training and ease of use of the systems	Adapted from Goodhue and Thompson (1995), Howard and Rose (2019), Swanson and Bellanca (2018) and adjusted to underground mine context.
	Location	Questions that explain if information on the system can easily be located	
	System quality	Questions that explain if information from the system is accurate, timely, and can easily be relied on	
	Authorisation	Questions explain if the system features can easily be accessed once authorised	
	User experiences	Questions explain if the workers' experiences of mobile SIC in the mining environment are positive	
	System reliability	Questions explain if the SIC is dependable and consistent	
	Safety	Questions explain if the system is effective and keeps workers safe	
	Compatibility	Questions explain if the SIC works well with other machines, systems, and the conditions of the mine	
	Task completion	Questions explain if the system gives accurate information that keeps workers safe	

*\*All scales were on Likert scale 7-1, anchored with "strongly agree" to "strongly disagree"*

#### **4.8 Data collection procedure**

A single data collection instrument, namely a survey questionnaire, was employed in this study. This survey approach is applicable to the online platform. The survey and questions were adapted from previous measures that have been used in TTF studies and adapted to the research context, as shown in Table 4.2.

Chevalier, Cloutier and Mitev (2019) discussed the advantages and disadvantages in using a questionnaire as the data collection instrument. They listed the benefits of using questionnaires as: (1) gaining feedback from dispersed users over a large area (2) users can respond to the questionnaire in their own time without interference (3) It is also easier to keep anonymity and confidentiality with responses to a questionnaire survey.

Meanwhile, the disadvantages of this tool, as depicted by Chevalier et al. (2019), are as follows: (1) A lengthy questionnaire may deter the respondents from completing it. (2) Furthermore, it is rather challenging to certain types of information, especially concerning sensitive topics. (3) Self-reported information gathered from questionnaires may be inaccurate or incomplete, seriously affecting research validity and reliability. (4) The quantitative research methods may be somewhat inflexible as the instruments cannot be modified after the study commences. (5) Errors from hypotheses testing in a quantitative study may yield misimpressions of program quality or influential factors. (6) Moreover, reducing data to numbers may lead to loss of information, while the wrong selection of procedures in determining statistical significance can result in erroneous findings, especially regarding impact.

The data collection instrument was constructed taking into consideration the advantages and disadvantages discussed by Chevalier et al. (2019). The instrument design selected reflected easier self-reporting, better tracking, anonymity, and easier data management for analyses. The instrument was built using a web-based survey tool called SurveyMonkey that offered web and mobile-based versions for data collection. Hence, the respondents could complete the survey regardless of their venue if they had Internet access.

The study used aspects of the data collection procedures discussed by Howard and Rose (2019). The study used a time-separated design resulting in the distribution of the questionnaire in two stages. As earlier discussed, first, the researcher started with the pilot data collection stage. The pilot survey was also treated as time 1 for the study and was distributed using SurveyMonkey with a target sample of 50 employees. The researcher sent an email to the participants informing

them of the purpose of the survey, attaching the link, and requesting respondents to access the link using either their desktop, mobile phone, or iPad devices. The structure of the questions enabled the collection of demographic and construct-related data. The scope of the SIC systems included all the systems they use, including mobile hardware devices, i.e., iPhone and iPads, and mobile applications such as the groundhog fleet management system, Microsoft Outlook, Deswik Scheduler, Cisco Webex teams, Microsoft Power BI, Mobilaris, etc. The users completed the questionnaire and returned, by email, their feedback regarding the structure of the questions, clarity on the meaning of questions, sentence construction, etc. The Pilot survey ran for four weeks, and the data was cleaned, coded, and both descriptive and the partial least squares structural equation modelling (PLS-SEM) analysis was completed. The results of the Time 1 or Pilot study also provided initial results for the understanding of the model and predictive relationships.

The second stage of the study was called Time 2 or the final survey stage. During this stage, the researcher modified the questions based on feedback from the respondents of the Pilot survey. The researcher sent a communication to all the 200 sampled employees with a link to the new survey. Follow-up emails were sent to the sampled employees' supervisors, who reminded their subordinates to complete the survey. This proved helpful in improving the survey completion rate as most of the sampled employees were busy with day jobs at the time of the survey.

#### **4.9 Data coding**

Following data collection, the data was exported from Survey Monkey to excel and coded accordingly following the naming rules for easier import in Smart PLS 3.3.3 (Ringle et al., 2015).

#### **4.10 Data analysis procedures and techniques**

The data collected by means of the questionnaire was analysed using two techniques: descriptive statistics and PLS-SEM.

The first approach involved using descriptive statistics, and the researcher used the IBM SSPS version 22 software package for this purpose. The descriptive analysis process involved preparing the data by coding the variables and labels in the software and ensuring the missing data was appropriately labelled. After that, different statistical methods were used to obtain descriptive statistics. These included running frequencies on the demographic data to

understand the representation of the sample. Further, cross-tabulations were run to understand how the variables cross-reference with other variables.

The second analysis was done using PLS-SEM. Smart PLS 3.3.3 (Ringle et al., 2015) assesses the measurement model and the structural model. According to Hair et al. (2017), structural equation modelling has been a well-known multivariate analysis method that applies statistical methods to analyse multiple variables simultaneously. They indicated that there are two primary structural equation modelling methods, namely exploratory and confirmatory, with the latter method confirming a priori established theories and concepts. The present research used PLS-SEM, a form of the exploratory method. It can identify patterns and relationships and better understand how the variables are related (Hair et al., 2017). PLS-SEM's ability as a second-generation multivariate statistical method to overcome the weakness of the first generation multivariate methods and incorporate unobservable variables measured indirectly by indicator variables has gained popularity in recent years among TTF researchers (Lin, 2014; Wu, Li & Fu, 2011). Harborth and Pape (2020) used PLS-SEM as proposed by many SEM scholars (Hair et al., 2017; Hair, Ringle, & Sarstedt, 2011) to understand cause-effect relationships between the latent (unobserved) variables and to predict the target constructs. For example, in the present study, the selected dependent and independent variables adapted a well-known TTF and TTF/M framework and the goal was to understand how independent variables better predictors of the dependent variables. Hair et al. (2017) explained that Smart PLS uses the PLS-SEM algorithm. They explained that this algorithm was initially developed by Wold (1975, 1982) and then further developed by Lohmöller (1989), Bentler and Huang (2014), Dijkstra (2014), and Dijkstra and Henseler (2015a, 2015b).

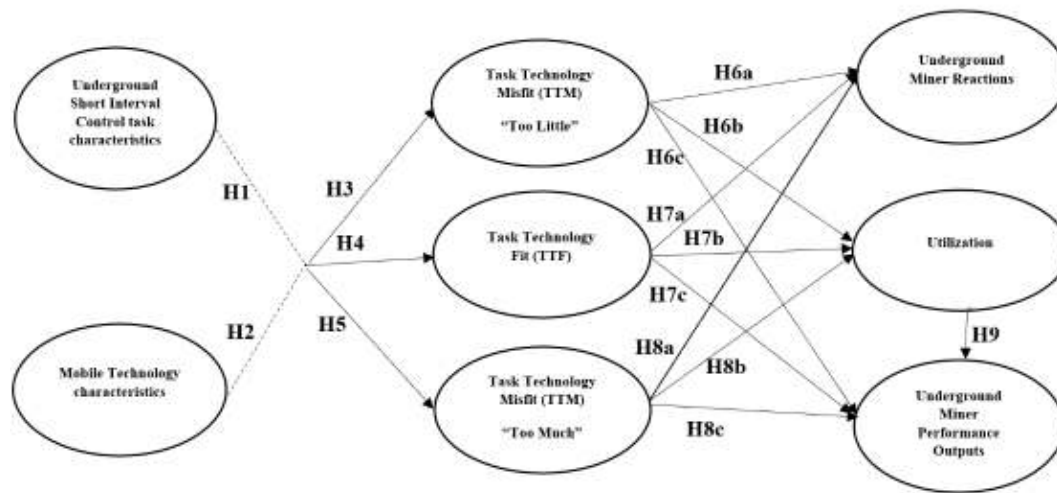
Further, they explained that the PLS-SEM algorithm estimates the path coefficient and another model parameter to maximise the explained variance of dependent constructs. Hair et al. (2017) explained that PLS-SEM is an OLS regression-based estimation technique that has statistical properties and focuses on predictions of a specific set of hypothesised relationships that maximise the explanation of variance in the dependent variables. Hair et al. (2017) quoted Chin (1998) to explain that structural equation modelling approaches such as PLS-SEM facilitate the measurement of errors in observed variables. McGill and Klobas (2009) also tested the relationships in the model using PLS-SEM. They explained that PLS-SEM provides an alternative estimation approach to traditional structural equation modelling (SEM). Hair et al. (2017) explained that PLS-SEM has constructs or latent variables, and each latent variable has

an indicator(s) or item(s) or observable variables. They explained that PLS-SEM makes use of the path models which they defined by quoting Samuel and Page (2016) as “diagram used to visually display the hypotheses and variable relationships that are examined when Sem is applied”. They further explained that the PLS path model has two elements, namely the structural model (inner model which represents relationships (paths) or hypotheses between constructs) and the measurement model (outer model which shows constructs and indicator variables. To perform PLS-SEM analysis, the present study followed the procedure proposed by Hair et al. (2017, p. 30). The following are the stages:

1. Specifying the structural model
2. Specifying the measurement model
3. Data collection and examination
4. Model estimation and the PLS-SEM algorithm
5. Evaluation of measurement models, i.e., reflective measurement models vs. formative measurement models
6. Evaluation of the PLS-SEM structural model results
7. Advanced PLS-SEM analyses
8. Interpretation of results and drawing conclusions.

#### **4.10.1 Stage 1: Specifying the structural model**

Hair et al. (2017) explained that this stage involves preparing a diagram that shows the research hypotheses and displays construct relationships to be examined. They said that this is rooted in the structural theory, which “show how the latent variables are related to each other”. In this study, the structural model was based on the new TTF/M model proposed by Howard and Rose (2019). See Figure 4.2 below.



**Figure 4.2: Structural model**

Source: Adapted from New Visual Representation of TTF Theory by Howard and Rose (2019)

As shown in Figure 4.2, the model's latent factors were adapted from previous proven models. Further, the predicted direct effects were justified because they are based on previous work by Goodhue and Thompson (1995) and Howard and Rose (2019) that established this precedence.

In the model above, the latent variables, namely underground short interval control task characteristics, mobile technology characteristics, the fit constructs, namely task-technology misfit (TTM) – “Too Little”, task-technology fit (TTF), task technology misfit –“Too Much” are the independent variables and also classified as exogenous variables. It is also important to note that underground miner reactions, utilisation, and performance outcomes serve as independent and dependent variables and are called endogenous variables. As shown in Figure 4.2, the relationships between constructs represent hypotheses to be tested, and these are called causal links as they represent predictive relationships. The structural model in this study has both mediating and moderating effects. Hair et al.(2017) explained that the mediating effect as "third construct" intervenes between two related constructs. For example, task-technology misfit (TTM) – “Too Little” mediates between underground short interval control task characteristics and underground miner reactions, utilisation, and underground miner performance outputs. Thus, task-technology misfit (TTM) – “Too Little,” task-technology fit (TTF), task-technology misfit – “Too Much” have a mediating effect on underground miner reactions, utilisation, and underground miner performance outputs.

The other relationships noticeable in the structural equation model are the direct effects which, according to Hair et al.(2017), are “relationships linking two constructs with a single arrow” and indirect effects, which are “sequence of two or more direct effects (compound path) presented visually by multiple arrows”. The model also has interactive effects where two or more constructs produce one effect on another variable. The interactive effects are also referred to as moderation by some scholars because the effect is the same. Hair et al.(2017) defined moderating effects as the “third variable that could directly alter the relationship between exogenous and endogenous latent variables in a different way”. In Figure 3.3, it can be seen that utilisation acts as a moderator in the relationship between task-technology misfit (TTF) – “Too Little”, task-technology fit (TTF), task-technology misfit – “Too Much” and underground miner reaction, performance outcomes respectively.

#### **4.10.2 Stage 2: Specifying the measurement model**

Hair et al. (2017) described this stage as determining the “relationships between constructs and their corresponding indicators variables”. The measurement model is also called the outer model. This follows the measurement theory, which Hair et al. (2017) said “specifies how the latent variables (construct) are measured”. The measurement model can be divided into two types, based on how the unobservable variables are measured. These are the formative measurement model and reflective model. For a formative measurement model, the directional arrows point from indicator variable to construct, indicating a causal or predictive relationship. However, for a reflective measurement model, the direction of the arrows is from the construct to the indicator variables and assumes that the construct causes the indicator variables. This study made use of the reflective models. As shown in Figure 4.3, the model was created using Smart PLS 3.3.3 (Ringle et al., 2015), the items or observable variables point towards the construct. For example, as SIC\_Task\_1, SIC\_Task\_2, SIC\_Task\_3 point towards the short interval control task characteristics construct. Adopting the reflective model over the formative model made sense as Hair et al.(2017) posited that the reflective measurement model is based on classic test theory where the measures represent the effect (or manifestation) of the underlying construct. Hair et al. (2017) argued that the reflective construct represents the construct's sample item domain. It is important to know that indicators are highly correlated, as explained by Hair et al.(2017), who quoted Nunnally and Bernstein (1994) and illustrated this by stating that the reflective measure indicates that the same construct causes the indicator items.

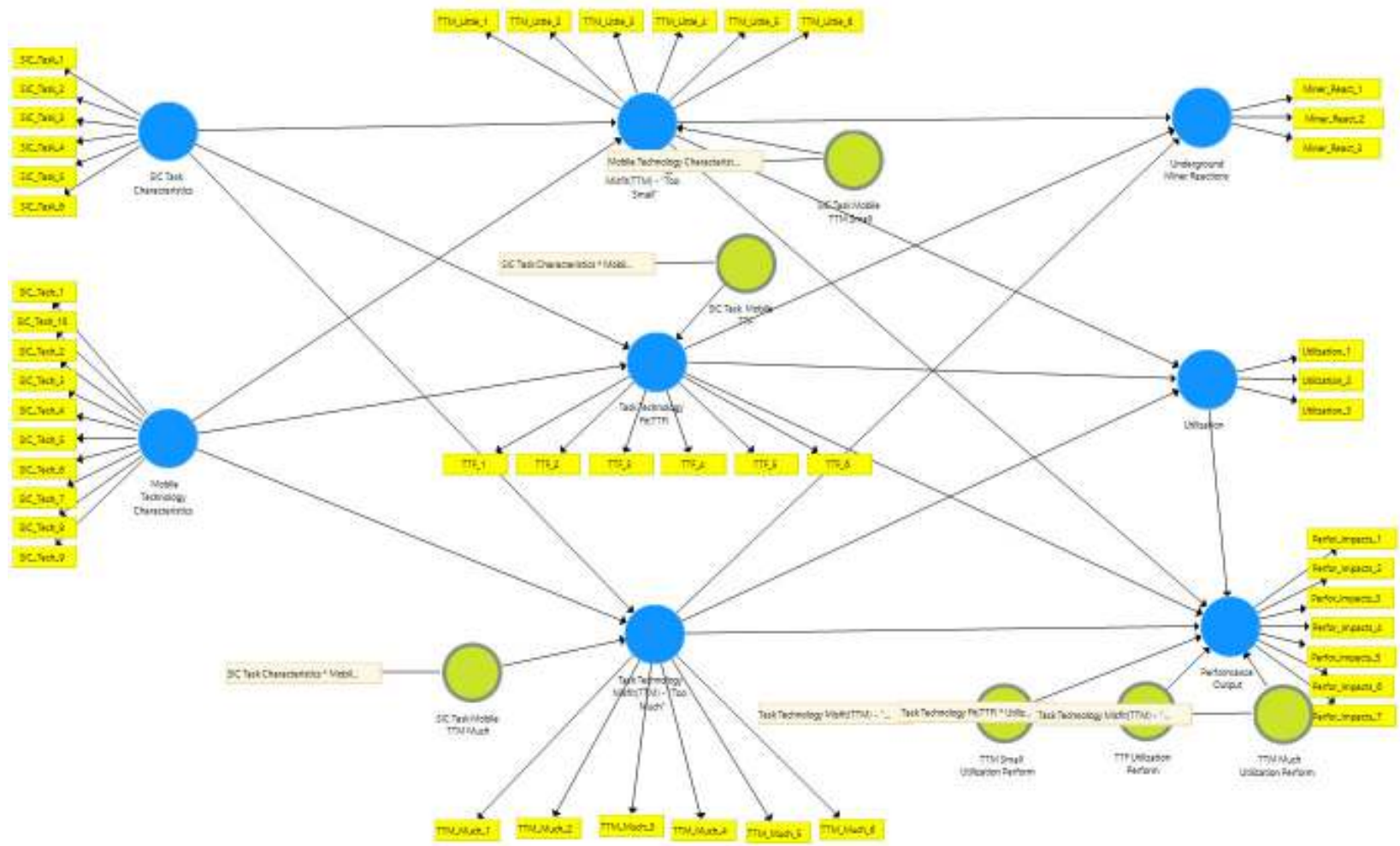


Figure 4.3: PLS model with structural and measurement models

### **4.10.3 Stage 3: Data collection and examination**

The researcher collected primary data from the sampled employees following the data collection procedure discussed earlier in this chapter. Once the data had been collected and downloaded from the SurveyMonkey system, the data was inspected to ensure it was correctly coded and cleaned in preparation for analysis.

The data cleaning process involved formatting the headers in the comma separated values (CSV) file where the data was stored, checking missing data, suspicious responses, outliers, and data distribution (Hair et al., 2017). The headers were formatted using short words. For example, observable variables on the indicators were rewritten. For short interval control characteristics, the headings were coded as SIC\_Task\_1, SIC\_Task\_2, SIC\_Task\_3, etc. This made the data acceptable in Smart PLS. Hair et al.(2017) explained that missing data occurs due to failure by the respondent to some questions. They explain that this might happen due to the sensitivity of the questions. The opt-out option was provided for in the present study, and the unanswered or skipped questions were coded as -99. As earlier stated, the present study, the analysis was conducted in Smart PLS 3 (Ringle et al., 2015). The option to use the mean value replacement was selected to handle missing data when the PLS-SEM model is run. According to Hair et al. (2017), the mean value replacement is a “missing value of an indicator variable that is replaced with the mean of valid values of the indicator”. They said that this should be used when the data has 5% values missing an indicator.

As part of data cleaning and preparation, the researcher examined the responses by looking at the data that was not coded, fixing it, and identifying any suspicious responses. Hair et al. (2017) pointed out some of the issues to be investigated: straight-lining, diagonal, and different alternative responses.

During descriptive analysis, some mean, variance, and distribution run also helped to identify suspicious patterns. Other things checked for were skewness, kurtosis which are measures of distribution, and understanding the symmetricalness of data.

Finally, outliers were also looked at, and because the responses were forced on the respondents, no extreme outlier was found. A detailed description of the data analysis stages 4 to 7 are discussed in Chapter 5, and Stage 8 is discussed in chapter 6.

#### **4.11 Reliability and validity of the study data**

In this study, indicator and internal consistency reliability were employed to determine data reliability and validity. The researcher adopted an approach advised by Lettig (2020) where data conclusions were evaluated against the criteria that determined “approximate suitability to ascertain the depth of deductions” compared to the validated research model. Lettig (2020) argued that reliability and validity are essential criteria for assessing methodologies. These form a crucial characteristic of a measurement procedure. A measurement is deemed to have reliability if it has no bias and thus will result in consistent measurement across time and various items in the instrument and therefore is stable and consistent with being replicable (Ritchie & Lewis, 2014; Sekaran & Bougie, 2013; Gaur & Gaur, 2009).

On the other hand, validity implies the measurement instrument measures the property it should measure. According to Lettig (2020), there are two types of validity, namely internal and external. The author quoted Ritchie and Lewis (2003) to explain that internal validity describes how well the collected data reflects the population. Lettig (2020) discussed external validity by referencing Miles et al. (2019), who said it is the chance to make general conclusions from the research and who argued that external validity increases relating cases to theory.

As earlier stated, the study used Smart PLS 3.3.3 (Ringle et al., 2015) to analyse the data using the PLS-SEM algorithm. Hair et al. (2017) said different reliability and validity measures exist for measurement (reflective or formative) and structural models.

The reflective model was used as a measurement model for this study. The quality of results was assessed by conducting reliability testing using internal consistency (using Cronbach's alpha and composite reliability), convergent validity (using indicator reliability, average variance extracted), and discriminate validity (using Fornell-lacker criterion, cross-loadings, and Heterotrait monotrait).

For assessing the structural model, as suggested by Hair et al.(2017), the researcher used collinearity assessment, structural model path coefficients, coefficient of determination ( $R^2$ ), the effective size of  $f^2$ , blindfolding, and predictive relevance  $Q^2$  and effect size of  $q^2$ .

#### **4.12 Research ethics considerations and conduct**

Research ethics has a crucial role in shaping a study to be of high value by adhering to the highest standards that result in acceptable research. This study adhered to the research ethics and standards stipulated in the Belmont Report, the university, and the Nevada Gold Mines. First, approval was sought from Nevada Gold Mines as per company policy on research partnership. The executive managing director, TRU general manager and general counsel approved the research project. The researcher also signed the non-disclosure agreement with Nevada Gold Mines. Second, the university research ethics committee approved the data collection process through the research supervisor. Third, as guided by the Belmont Report, the questionnaire allowed the sample group members to select opt-out as part of the responses. The respondents did not provide their names for confidentiality and anonymity purposes.

#### **4.13 Research method assumptions, delimitations, and limitations**

This study assumed that the underground miners at Turquoise Ridge underground division used mobile devices and apps that the company provided to execute SIC tasks. An assumption was also made that these mobile devices and apps were used in an underground setting with network connections.

The delimitation for this study includes the specific parameters used. The study was conducted at the Turquoise Ridge underground division. The target population was all the underground miners assigned with mobile devices (e.g., iPad, iPhones, and mobile apps) to use the SIC. The stratified sampling technique was applied to ensure equal representation from the different crews of miners. The data collection instrument was designed by adopting items from past TTF studies.

This study has several drawbacks. First, the influence of several factors could not be avoided, such as a restricted research timeline to complete the survey. Despite the double execution employed in this study and item refinement, respondents' self-reporting might have yielded a slightly different understanding towards some questions. The study was conducted in the underground division, whereby the mining methods and processes may differ from a surface or open-pit division. Hence, the results are generalisable to underground mines only.

#### **4.14 Chapter conclusion**

This chapter presented the research design that was deemed suitable for this study. The hypothetical inductive approach resulted in using the TTF theory for hypotheses formulation using data from the case study. Both the positivism research philosophy and quantitative approach are discussed in detail. The chapter describes and provides justification to the data collection and analysis methods selected. The research design adhered to high standards of research ethics thus strongly supporting addressing the research question.

### 5.1 Chapter introduction

The chapter presents the data analysis and research findings. The purpose of the study was to quantitatively assess and suggest improvements to the TTF/M between SIC task characteristics and mobile technology characteristics in predicting individual performance outcomes of miners, utilisation, and individual miner reactions. The assessment of task technology fit has historically been done using the Goodhue and Thompson (1995) TTF model and other extensions. In this study, the researcher used the extended TTF model proposed by Howard and Rose (2019), which suggests the inclusion of task-technology misfit constructs. The study used a hypothetical-deductive design as discussed in Chapter 4 and collected data from 106 respondents. Therefore, in this chapter, the researcher presents the data analysis results for descriptive statistical analysis and partial least squares – structural equation modeling (PLS-SEM). It ends with a chapter conclusion.

### 5.2 Descriptive findings and analysis

The researcher used the IBM SPSS version 22 to perform descriptive data analysis. The results from the data analysis are presented as charts, tables, and graphs.

#### 5.2.1 Demographics

As discussed in Chapter 4, a total of 200 underground miner employees were purposively sampled for this study. The total number of respondents to the survey was 106(N=106) representing a 53% response rate. The participants covered a broad spectrum of age, employee category, position level in the organisation, experience, education backgrounds and departments. Specifically, the response rate was 73.6% male and 24.5% female. The age groups were well distributed with the 30-39 (31.1%) age group representing most of the miners in the sample, followed by those from 20-39 (23.6%) and >39 representing 31.1%.

Most of the respondents were hourly employees and made up of 60.4% and salary employees were 37.7%. The sampled employees who had less than a year working experience in the mines represented 6.6%, 1 to 5 years were 26.4%, and 6 to 10 years were 21.7%. The majority (42.5%)

had more than 10 years of working experience in the mines. Table 5.1 shows a summary of the demographic characteristic of the sample (N = 106).

**Table 5.1: Summary of demographic characteristics of sample (N = 106)**

<b>Demographic</b>	<b>Category</b>	<b>Frequency</b>	<b>Percentage</b>
Gender	Male	78	73.6
	Female	26	24.5
	Opt Out	2	1.9
Age	20-29	25	23.6
	30-39	43	40.6
	>39	33	31.1
	Opt-Out	5	4.7
Employee Category	Hourly	64	60.4
	Salary	40	37.7
	Opt-Out	2	1.9
Position Level in organization	Top Management (e.g., Managers, GM etc.)	3	2.8
	Middle Management (e.g., General Supervisors, Superintendents etc.)	7	6.6
	Technical Services (e.g., Mine Engineers, Geologists, Surveyors, Geotech etc.)	23	21.7
	Front Line Supervisors (e.g., Supervisors, Leadman)	8	7.5
	General (Underground Miner, Operator, Maintenance etc.)	52	49.1
	Opt-Out	13	12.3
Experience	Less than a year	7	6.6
	1 to 5 years	28	26.4
	6 to 10 years	23	21.7
	More than 10 years	45	42.5
	Opt-out	3	2.8
Education	High School Diploma	55	51.9
	Associate Degree	8	7.5
	Bachelor's degree	25	23.6
	Graduate degree	9	8.5
	Opt-out	9	8.5
Department	Underground Mining Operations	56	52.8
	Engineering	15	14.2

<b>Demographic</b>	<b>Category</b>	<b>Frequency</b>	<b>Percentage</b>
	Health, Safety and Environment	17	16.0
	Administration i.e., HR, IT, Supply Chain etc.	14	13.2
	Opt-out	4	3.8

### **5.3 PLS-SEM findings and analysis**

Many researchers (Hair et al., 2011; Pallud, 2017) reference the guidelines by Gefen, Straub and Boudreau (2000) who recommended that when using partial least squares (PLS), the minimum sample size required should be "10 times the number of items in the most complex construct". In the model for this study, the complex model is mobile characteristics which has 10 items and thus the minimum sample size would be 100 participants. The realised sample in this study is 106 which is above the minimum hence meeting the requirement recommended by Gefen et al. (2000).

In Chapter 4, the researcher completed some stages of PLS-SEM analysis, namely specifying the structural model (Stage 1) and measurement model (Stage 2), data collection and examination (Stage 3) following the stages of applying PLS-SEM as proposed by Hair et al. (2017, pp. 37–47). In this section, a detailed explanation of PLS-SEM using Smart PLS 3.3.3 (Ringle et al., 2015) is discussed in stages 4 to 5. The application of PLS-SEM continues in this chapter with the focus on the last three steps, namely model estimation, and the PLS-SEM Algorithm (Stage 4), evaluation of measurement models, i.e. reflective measurement models vs. formative measurement models (Stage 5) and evaluation of the PLS-SEM structural model results (Stage 6).

#### **5.3.1 Stage 4: PLS path model estimation**

In Stage 4, the data which was formatted in a CSV file was loaded in Smart PLS 3.3.3 (Ringle et al., 2015) through the import functionality. The measurement and structural model were created as depicted in Figure 3.3. The PLS algorithm was executed, and the model was tested using Smart PLS 3.3.3 (Ringle et al., 2015). As per the advice from Harborth and Pape (2020), the researcher chose the path weighting scheme with a maximum of 300 iterations and a stop criterion of  $10^{-7}$  and then proceeded to run the PLS algorithm,

Next, the researcher followed the suggestion by Harborth and Pape (2020) and performed a reflective measurement model and structural model evaluation by looking at reliability and validity of the results before interpreting them.

### **5.3.2 Stage 5: Evaluation of reflective measurement models**

Before performing a detailed analysis of the reflective measurement model results, the researcher looked at the outer loadings and weights. According to Hair et al. (2011), the outer loadings are supposed to be a minimum of 0.7. Following the guidance by Bagozzi, Yi and Phillips (1991), the items or observable variables with loadings  $< 0.7$  were dropped considering the rule of only dropping 20% of the observable variables. This process was repeated across different constructs, resulting in better reliability and validity of the model. As suggested by Harborth and Pape (2020), the evaluation or assessment of this reflective measurement model included internal consistency reliability, convergent validity, and discriminant validity.

#### ***Internal consistency reliability***

Hair et al. (2017) explained that internal consistency reliability should be evaluated first using its traditional criterion, Cronbach's alpha, which estimates the reliability based on inter-correlations of the observed indicator variables. Harborth and Pape (2020) defined internal consistency reliability as a measurement that "indicates how well certain indicators of a construct measure the same latent phenomenon". Hair et al. (2017) reckoned that Cronbach's alpha has some limitations. For this reason, another measure of internal consistency reliability, called composite reliability should be used as it considers different outer loadings of the indicator variables. They explained that both Cronbach's  $\alpha$  and the composite reliability values should be between 0.7 and 0.95 for the research that builds upon accepted models. Harborth and Pape (2020) quoted Hair et al. (2017) in explaining that the values of Cronbach's  $\alpha$  are seen as a lower bound and values of the composite reliability as an upper bound of the assessment. Table 5.2 shows the internal consistency reliability for the variables.

**Table 5.2: Internal consistency reliability**

<b>Latent variable</b>	<b>Cronbach's alpha</b>	<b>Composite reliability</b>
Mobile technology characteristics	0.934	0.945
Performance output	0.982	0.985
SIC task characteristics	0.936	0.95
Task-technology fit (TTF)	0.960	0.968
Task-technology misfit (TTM) – "Too Much"	0.946	0.957
Task-technology misfit (TTM) – "Too Little"	0.936	0.95
Underground miner reactions	0.891	0.934
Utilisation	0.896	0.935

As shown in Table 5.2, all values for Cronbach's  $\alpha$  are above the lower threshold of 0.7 and below upper threshold of 0.95 except for performance output and TTF which has Cronbach's  $\alpha$  0.98 and 0.96 respectively. For composite reliability, a value is above the lower threshold of 0.7. As in Cronbach's  $\alpha$ , there are some variables with a composite reliability above 0.95 because they have indicators measuring the same dimension of the latent variable (Hair et al., 2017). Based on the analysis of Cronbach's alpha and composite reliability, the internal consistency reliability in the present research was found not to be an issue across all the latent variables.

### ***Convergent validity***

Harborth and Pape (2020) referred to convergent validity as the number that determines the "degree to which that construct explains indicators of a certain reflective construct". According to Hair et al. (2017), the criterion is "the grand mean value of the squared loadings of the indicators associated with the construct (i.e., sum of squared loadings divided by the number of indicators)". They explained that the convergent validity is measured at construct level using the average variance extracted (AVE). Hair et al. (2017) said that the rule of the thumb is for the AVE value to be above 0.50 or higher as the indicators with a high value explain more than half of the indicator variance. However, if AVE is less than 0.50, the indicators are average and more variances remain in the error of its value being explained by the construct. Table 5.3 shows the AVE values for each latent variable.

**Table 5.3: Average variance extracted (AVE)**

<b>Latent variable</b>	<b>AVE</b>
Mobile technology characteristics	0.634
Performance output	0.902
SIC task characteristics	0.759
Task-technology fit (TTF)	0.834
Task-technology misfit (TTM) – "Too Much"	0.789
Task-technology misfit (TTM) – "Too Little"	0.759
Underground miner reactions	0.825
Utilisation	0.827

As shown in the Table 5.3, all AVE values of this study were above 0.5, thus demonstrating convergent validity.

#### ***Discriminant validity***

Harborth and Pape (2020) and Hair et al. (2017) agreed that discriminant validity is a measure that explains how the constructs are different from other constructs using empirical standards. According to Hair et al. (2017), when discriminant validity is established, it implies that a construct is unique and captures the phenomenon that other models have not covered. According to Harborth and Pape (2020), there are two approaches to determining discriminant validity assessment. The first approach involves assessing cross-loadings and checking if all latent variable or construct outer loadings are larger than its cross-loadings with other latent variables or constructs (Hair et al., 2017). As per the cross-loadings table in Appendix B, all cross-loadings are smaller than the outer loadings and following the rule of thumb suggested by Hair et al. (2017), this fulfils the discriminant validity.

The second approach discussed by Harborth and Pape (2020) is called the Fornell-Larcker criterion. This approach is on the construct level and compares the square root of the constructs' AVE with the correlations with other constructs. The authors quoted Hair et al. (2017) who explained that in this second approach, as a rule of thumb, the square root of the AVE of a single construct should be larger than the highest correlation with other constructs. Hair et al. (2017) stated that the alternative is to evaluate the Fornell-Larcker criterion by determining whether the AVE is larger than the squared correlation with any other constructs. As per the

table in Appendix C, the values are larger than the correlations with other constructs, indicating discriminant validity.

Henseler et al. (2014) referred to some performance issues with measuring discriminant validity using cross-loadings and the Fornell-Larcker criterion. Hair et al. (2017) pointed out that the issues were because cross-loadings fail to indicate a lack of discriminant validity when the constructs are perfectly correlated. They argued that the Fornell-Larcker criterion tends to have performance issues when indicator loadings of constructs that are being investigated differ slightly, that is the indicator loading is different between 0.60 and 0.80. They explained that the Fornell-Larcker criterion only shows improvements in performance in different discriminant validity issues when the improved indicator loadings vary more strongly.

Following the issues noted with cross-loadings and the Fornell-Larcker criterion, Henseler et al. (2014) proposed using the heterotrait-monotrait ratio (HTMT) of correlations. They explained that HTMT is a “ratio of between trait correlations to the within trait correlations”. Harborth and Pape (2020) explained what the measure of the true correlation of two constructs would be if the measurement is flawless (Hair et al., 2017). HTMT as explained by Hair et al. (2017) is a means of all correlations of indicators’ cross constructs measuring different constructs, i.e. heterotrait-heteromethod correlations. This is relative to the geometric mean of average of indicators measuring the same construct. As a rule of the thumb, researchers explain that values close to 1 for HTMT indicate a lack of discriminant validity and a conservative threshold is 0.85 (Harborth & Pape, 2020; Hair et al, 2017).

**Table 5.4: Heterotrait-monotrait ratio (HTMT) of correlations**

Latent variable	1	2	3	4	5	6	7	8
1.Mobile technology characteristics								
2.Performance output	0.572							
3.SIC Task characteristics	0.588	0.633						
4.Task-technology fit (TTF)	0.678	0.673	0.442					
5.Task-technology misfit (TTM) – "Too Much"	0.456	0.462	0.208	0.688				
6.Task-technology misfit (TTM) – "Too Little"	0.468	0.42	0.247	0.685	0.763			
7.Underground miner reactions	0.769	0.605	0.618	0.758	0.473	0.518		
8.Utilisation	0.786	0.633	0.47	0.842	0.618	0.548	0.838	N/A

Table 5.4 contains HTMT values, and no value is above the threshold of 0.85. As suggested by researchers (Harborth & Pape, 2020; Hair et al., 2017), apart from looking at HTMT ratios, the researcher tested how significantly HTMT statistics differ from 1. In the present study, this required using the bootstrapping option in Smart PLS 3.3.3 (Ringle et al., 2015) with the procedure using 5,000 subsamples to get the confidence interval in which the true HTMT value lies with a 95% chance. Hair et al. (2017) stated that as a rule of the thumb, the HTMT measure requires that no confidence interval contains the value 1. As can be seen in the table in Appendix D, no measure has a confidence interval 1 and the HTMT ratio is below 0.85 – thus discriminant validity is established for the model.

### **5.3.3 Stage 6: Evaluation of the PLS-SEM structural model results**

The previous stage allowed the researcher to evaluate the reflective model. In Stage 6, the focus was on evaluating the structural model which represents the underlying TTF/M model used in the study and adapted from Howard and Rose (2019). According to Hair et al. (2017), the assessment of the structural model results allows for knowing how capable the model can predict one or more target constructs. In the present study, this allowed the researcher to understand the interaction of SIC task and mobile technology characteristics and their relationship with TTM – “Too Little”, TTF and TTM – “Too Much”. Further, the study investigated how utilisation moderates the relationships between TTM – “Too Little”, TTF and TTM – “Too Much” and underground miner reaction, utilisation and underground miner performance outcomes. The study adopted the structure model assessment procedure proposed by Hair et al. (2017) which includes PLS-SEM model fit measures, collinearity assessment, structural model path coefficients, coefficient of determination ( $R^2$ ), effect size of  $f^2$ , blindfolding and predictive relevance  $Q^2$  and coefficient size of  $q^2$ .

#### ***PLS-SEM model fit measures***

General structural equation modelling fit measures are determined using different statistics. In order to check the statistical fitness, Hu and Bentler (1999) prescribed (1) chi-square or minimum function test statistics and a better test is when it is not significant for  $p < .05$ , but significantly affected by sample size, (2) comparative fit index (CFI), and (3) Tucker-Lewis index (TLI) with satisfactory and ideal values at  $> .9$  and ideally  $> .95$ , respectively (closer to 1 is better), (4) root mean square error of approximation (RMSEA) with satisfactory and ideal values at  $< .6$  (closer to 0 is better), and (5) standardised root mean squared residual (SRMR) that should not exceed  $.8$  (closer to 0 is better).

Although the discussion of the PLS-SEM Model fit measures is not stated as a step in the structural model assessment procedure by Hair et al. (2017), they indicate it as a step to be aware of even though they warn that researchers should be cautious not to report and use model fit in PLS-SEM. Smart PLS 3.3.3 (Ringle et al., 2015) offers some fit measures: SRMR, exact fit criteria  $d\_ULS$  and  $d\_G$ , NFI,  $Chi^2$ , RMS\_theta.

According to SmartPLS (2021), SRMR is calculated by transforming the sample covariance matrix into correlation matrices. They observed that covariance is equal to the model covariance plus the SRMR. Doing this enables comparisons to be made between observed and expected correlations on their absolute scale. According to Hu and Bentler (1999), a root mean squared residual of 0.08 is preferable. Henseler et al. (2014) introduced the SRMR as a measure for PLS that is ideal for that task.

SmartPLS (2021) explains that the  $d\_ULS$  (i.e, the squared Euclidean distance) and  $d\_G$  (i.e. the geodesic distance) is equivalent to the measure of discrepancy (Dijkstra & Henseler, 2015a). The bootstrap process provides confidence intervals. The  $d\_G$  model is built on PLS-SEM values. Hair et al. (2017) stated that the question remains: How do these values differ from CB-SEM?  $d\_ULS$  and  $d\_G$  do not stand for anything in particular. Only bootstrap outcomes can be interpreted. Specifically, since the normal bootstrap does not calculate the  $d\_ULS$  and  $d\_G$  (and SRMR) confidence intervals, but the adapted Bollen procedure, their meaning is slightly different. For the exact fit criteria (i.e,  $d\_ULS$  and  $d\_G$ ), one would calculate the range as the confidence interval from the samples. The confidence interval should include the value itself. Thus, the upper bound for the interval represents a “good fit”. It is necessary to try and choose an interval that spans from 95% to 99% confidence. Meaningfully, in other words, if your model fits well, your correlation matrix and empirical matrix are nearly the same. Thus, the model-implied correlation should be different from the empirical correlation ( $p > 0.05$ ). In that case, if the model doesn't fit the data, the result is inconclusive.

According to SmartPLS (2021), the normed fit index (NFI) or Bonett and Bentler was one of the first indices for measuring a model fit by Bentler and Bonett (1980). It computes the  $Chi^2$  of the model and compares it to a relevant reference model. Even though the  $Chi^2$  value is not reliable, the NFI uses the  $Chi^2$  value from the null model. The NFI values range from 0 to 1. The closer the NFI is to 1, the better. According to Smart PLS (2021), Lohmöller (1989) provides detailed information on the NFI computation of PLS path models. They explain that the NFI is still under development.

Further, according to SmartPLS (2021), for  $\chi^2$  and degrees of freedom, assuming a multi-normal distribution, the  $\chi^2$  of a PLS model with df approximately equals  $(N-1) * L$ , where N is the number of observations and L the maximum likelihood function, as defined by Lohmöller (1989). In the PLS path model, the degrees of freedom are represented as  $(K^2 + K) / 2 - t$ , or the number of independent parameters is reduced by dividing the total number of variables. The explanation provided is that it will be necessary to definitively determine degrees of freedom of composite models, common factor models, and mixed models when using PLS-SEM in future research (SmartPLS, 2021).

SmartPLS (2021) quoted Lohmöller (1989) to explain that the RMS\_theta is the root mean squared residual covariance matrix of the outer model residuals. Outer model residuals have no meaning when used for formative assessment purposes. The RMS\_theta uses the outer model residuals, which are the differences between predicted values and observed values. The closer to zero you can get, the better. The topic needs to be further refined in terms of PLS and SEM. Low values indicate a good model fit, while above 0.14 indicates poor model fit (Henseler et al., 2014).

According to SmartPLS (2021), the PLS-SEM model fit measures is only at the very beginning stages. The computation, usage, and interpretation of these outcomes in future research should be discussed. PLS-SEM literature on the estimation and saturation criteria is vague, though they can be defined as "usefulness" or "validity". However, the estimated model appears to be a sound, even if the PLS path model fit results are a subject for discussion.

While adhering to the warning given by PLS-SEM scholars (Hair et al., 2017; Lohmöller, 1989) decided to check these fit measures, to look at the results and interpret them within the context of the known rules of the thumb.

**Table 5.5: PLS-SEM fit measures**

Fit measure	Saturated model	Estimated model
SRMR	0.077	0.172
d_ULS	6.741	33.472
d_G	5.720	n/a
Chi-square	2372.262	1791.822
NFI	0.686	0.763

\*\*\* rms Theta 0.157

As can be seen in Table 5.5 above which shows the PLS-SEM fit measures, the structural model and estimated model, some measures have an acceptable fit (chi-square=2372.262 with 146 d.f.; NFI=0.686; SRMR=0.077; d\_ULS= 6.741; d\_G= 5.72; rms Theta = 0.157) and others do not. Hair et al. (2017) argued that fit statistics should not be used routinely for PLS-SEM. Although these fit measures sacrifice much predictive power, they claim it offers good results. The use of PLS-SEM fit measures is still in the early phases of research and should be interpreted with caution (Hair et al., 2017).

### ***Collinearity assessment***

After checking the fit, the bootstrapping procedure was run with the setting put to 5000 bootstrap subsamples. This resulted in the updated PLS-SEM results that needed further assessment to evaluate the structural model. The collinearity assessment was conducted as a first step. Harborth and Pape (2020) explained that collinearity happens when two predictor variables are highly correlated. Hair et al. (2017) said that it is called multicollinearity when two or more indicators are involved. They further said that high collinearity is an issue because it impacts the estimation of weights and their significance. Thus, to address collinearity, an assessment of inner variance inflation factor (VIF) was performed. One the issues addressed by collinearity assessment in PLS-SEM is common method bias (Kock, 2015). Common method bias is a "phenomenon that is caused by the measurement method used in an SEM study, and not by the network of causes and effects among latent variables in the model being studied" (Kock, 2015). Kock (2015) explained this by giving an example, "the instructions at the top of a questionnaire may influence the answers provided by different respondents in the same general direction, causing the indicators to share a certain amount of common variation". The process to address collinearity issues involves examining each set of predictor constructs separately or outer and inner sub-parts of the structural model. Hair et al. (2017) said the rule of thumb is for each predictor construct's VIF to be above 0.20 but lower than 5 as this indicates that collinearity between constructs is not present.

Initially when the PLS algorithm was executed, some indicators on miner reaction, performance impacts and TTF had an inner VIF above 5. Hair et al. (2017) suggested that treating collinearity issues in the data requires the elimination of constructs, merging constructs or creating high order constructs. In this study, eliminating the constructs was used to achieve the VIF, listed in Table 5.6, thus ensuring there are no collinearity issues in the model.

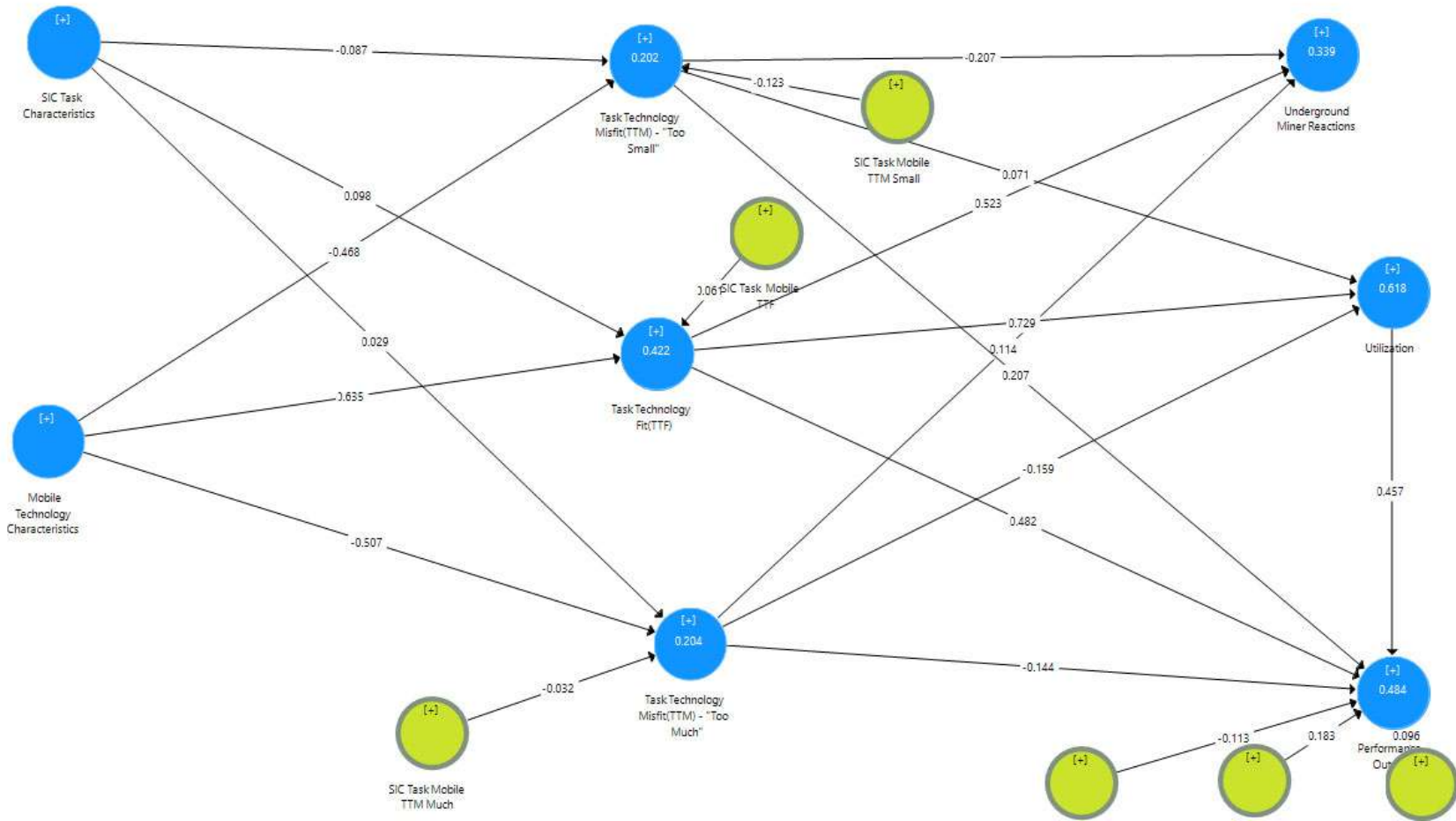
**Table 5.6: Inner variance inflation factor (VIF)**

Indicator	VIF
Miner React 1	1
Perfor_Impacts_1	3.149
Perfor_Impacts_2	3.149
SIC Task 1	3.397
SIC Task 2	4
SIC Task 4	2.434
SIC Task 5	3.34
SIC Task 6	2.202
SIC Tech 1	2.056
SIC Tech 2	2.337
SIC Tech 3	2.312
SIC Tech 4	2.804
SIC Tech 5	3.349
SIC Tech 6	2.227
SIC Tech 7	2.039

Indicator	VIF
TTF 1	4.666
TTF 2	4.797
TTF 3	3.149
TTF 4	3.41
TTF 5	4.512
TTM Small 1	2.942
TTM Small 2	2.655
TTM Small 3	2.774
TTM Small 4	4.347
TTM Small 5	3.96
TTM Small 6	4.572
TTM Much 1	2.91
TTM Much 2	2.032
TTM Much 3	3.599
TTM Much 4	2.811
Utilisation 1	2.774
Utilisation 2	2.709
Utilisation 3	2.682

***Structural model path coefficient***

Figure 5.1 below is the structural model with path coefficients after running the PLS-SEM algorithms. The figure illustrates the results of the path estimations and the adjusted R<sup>2</sup>-values of the endogenous variables.



\*\* Too Little is also referred to as Too Small in above figure

**Figure 5.1: Structural model results**

As per recommendation by Hair et al. (2017), the researcher first did an assessment of path coefficient to ensure standardized values between -1 and +1. Hair et al. (2017) explained that the path coefficients close to +1 represent a strong positive relationship and those close to -1 represent a strong negative relationship. The closer the estimated coefficients are to 0, the better the relationships are.

Second, the research proceeded to check the significance of the path coefficient. Here, as per Hair et al. (2017), the bootstrapping routine was applied. The minimum number of bootstrap samples was set to 5000 with a value for a two-tailed test set to 1.96 (significance level =5%). They said that 1.96 is considered a critical value and if this coefficient is smaller than  $p < 0.05$ , it is significant. The bootstrapping technique implemented in Smart PLS 3.3.3 (Ringle et al., 2015) was used to evaluate the significance of these hypothesised relationships. Table 5.7 shows the  $p$  values and decisions regarding the hypotheses.

**Table 5.7: Path coefficient significance results**

Relationship or hypothesis	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T Statistics ( O/STDEV )	P Values	Decision
H1a: SIC task characteristics -> Task-technology misfit (TTM) – "Too Little"	-0.087	-0.105	0.123	0.709	0.478	Not Supported
H1b: SIC task characteristics -> Task-technology fit (TTF)	0.098	0.121	0.114	0.862	0.389	Not Supported
H1c: SIC task characteristics -> Task-technology misfit (TTM) – "Too Much"	0.029	0.014	0.113	0.259	0.796	Not Supported
H2a: Mobile technology characteristics -> Task-technology misfit (TTM) – "Too Little "	-0.468	-0.47	0.097	4.849	0.000	Supported
H2b: Mobile technology characteristics -> Task-technology fit (TTF)	0.635	0.628	0.107	5.917	0.000	Supported
H2c: Mobile technology characteristics -> Task-technology misfit (TTM) – "Too Much"	-0.507	-0.513	0.093	5.482	0.000	Supported
H3: SIC task characteristics * mobile characteristics -> Task-technology misfit (TTM) – "Too Little"	-0.123	-0.134	0.067	1.847	0.065	Not Supported
H4: SIC task characteristics * mobile characteristics-> Task-technology fit (TTF)	0.061	0.065	0.062	0.998	0.318	Not Supported
H5: SIC task characteristics * mobile characteristics-> Task-technology misfit (TTM) – "Too Much"	-0.032	-0.041	0.064	0.494	0.622	Not Supported

Relationship or hypothesis	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T Statistics ( O/STDEV )	P Values	Decision
H6a: Task-technology misfit (TTM) – "Too Little" -> Underground miner reactions	-0.207	-0.205	0.173	1.195	0.232	Not Supported
H6b: Task-technology misfit (TTM) – "Too Little" -> Utilisation	0.071	0.089	0.1	0.716	0.474	Not Supported
H6c: Task-technology misfit (TTM) – "Too Little" -> Performance output	0.207	0.14	0.175	1.181	0.238	Not Supported
H7a: Task-technology fit (TTF) -> Underground miner reactions	0.523	0.535	0.132	3.968	0.000	Supported
H7b: Task-technology fit (TTF) -> Utilisation	0.729	0.728	0.104	6.985	0.000	Supported
H7c: Task-technology fit (TTF) -> Performance output	0.482	0.431	0.223	2.156	0.031	Supported
H8a: Task-technology misfit (TTM) – "Too Much" -> Underground miner reactions	0.114	0.121	0.14	0.816	0.414	Not Supported
H8b: Task-technology misfit (TTM) – "Too Much" -> Utilisation	-0.159	-0.177	0.107	1.483	0.138	Not Supported
H8c: Task-technology misfit (TTM) – "Too Much" -> Performance output	-0.144	-0.104	0.211	0.682	0.495	Not Supported
H9a: Task-technology misfit (TTM) – "Too Little" * utilisation -> Performance output	-0.113	-0.023	0.275	0.411	0.681	Not Supported
H9b: Task-technology misfit (TTM) – "Too Much" * utilisation -> Performance output	0.096	0.055	0.277	0.346	0.730	Not Supported
H9c: Task-technology fit (TTF) * utilisation -> Performance output	0.183	0.18	0.204	0.894	0.371	Not Supported
H9d: Utilisation -> Performance output	0.457	0.503	0.231	1.981	0.048	Supported

As the results show in Table 5.10, all hypothesised paths were not significant except for the following which were significant ( $p < 0.05$ ): mobile technology characteristics positively impact task-technology fit (TTF), mobile technology characteristics positively impact task-technology misfit (TTM) – "Too Much", mobile technology characteristics positively impact task-technology misfit (TTM) – "Too Little", task-technology fit (TTF) predicts performance output, task-technology fit (TTF) predicts underground miner reactions, task-technology fit (TTF) positively impacts utilisation and utilisation positively impacts performance output.

According to Hair et al. (2017), bootstrap confidence intervals provide information on the stability of the coefficient. The confidence interval bias corrected table is shown in Appendix

D. The other considerations for assessing the relevance of significant relationships included checking the path coefficients and interpreting them relative to each other. As an example, if the path coefficients were significant, like the ones discussed previously, checking which path coefficient was larger than the other would explain that its effect on the endogenous latent variable was greater. However, if the path coefficient was zero, then the value indicates the extent to which the exogenous construct is associated with the endogenous construct.

In assessing the direct, indirect, interactive, moderating and total effects of the relationships, the considerations would be great as these would provide more explaining to understand the paths for the relationships. Hair et al. (2017) explained that for direct with direct effect, one construct affects another construct. Specific examples from the model include the effect of mobile technology characteristics on task-technology fit (TTF). The indirect effect refers to a situation where one construct affects another construct via a mediating construct. For example, the effect of mobile technology characteristics on utilisation which goes through TTF, TTM- “Too Little”, TTF- “ Too Much”. The total effect is the sum of the direct and indirect effects.

**Table 5.8: Indirect effects results**

*Indirect effects*

<b>Construct</b>	<b>Mobile technology characteristics</b>	<b>Performance output</b>	<b>Underground miner reactions</b>	<b>Utilisation</b>
Mobile technology characteristics		0.515	0.371	0.51
Performance output				
SIC task mobile TTF		0.05	0.032	0.045
SIC task characteristics		0.053	0.073	0.061
SIC task mobile TTM – “Too Much”		0.007	-0.004	0.005
SIC task mobile TTM - "Too Little"		-0.03	0.025	-0.009
TTF utilisation perform				
TTM – “Too Much” utilisation perform				
TTM - "Too Little" utilisation perform				
Task-technology fit (TTF)		0.333		
Task-technology misfit (TTM) – "Too Much"		-0.072		
Task-technology misfit (TTM) – "Too Little"		0.033		
Underground miner reactions				
Utilisation				

**Table 5.9: Total effects results**

*Total Effects*

<b>Construct</b>	<b>Performance output</b>	<b>Task-technology fit (TTF)</b>	<b>Task-technology misfit (TTM) – "Too Much"</b>	<b>Task-technology misfit (TTM) – "Too Little"</b>	<b>Underground miner reactions</b>	<b>Utilisation</b>
Mobile technology characteristics	0.515	0.635	-0.507	-0.468	0.371	0.51
Performance output						
SIC task mobile TTF	0.05	0.061			0.032	0.045
SIC task characteristics	0.053	0.098	0.029	-0.087	0.073	0.061
SIC task mobile TTM – "Too Much"	0.007		-0.032		-0.004	0.005
SIC task mobile TTM - "Too Little"	-0.03			-0.123	0.025	-0.009
TTF utilization perform	0.183					
TTM- "Too Much" utilisation perform	0.096					
TTM - "Too Little" utilisation perform	-0.113					
Task-technology fit (TTF)	0.815				0.523	0.729
Task-technology misfit (TTM) – "Too Much"	-0.216				0.114	-0.159
Task-technology misfit (TTM) – "Too Little"	0.24				-0.207	0.071
Underground miner reactions						
Utilisation	0.457					

The study also analysed the mediating effect. As evident from the structural model, TTF, TTM- “ Too Little”, TTM-“ Too Much” and utilisation were mediating constructs in the model. The present study and model were adapted from the model proposed by Howard and Rose (2019) and thus the study had a prior theoretical support for the mediating effect analysis.

It is argued that interactive effect is modelled the same way as the moderating effect (Hair et al., 2017). In the structural model in this study, SIC characteristics and mobile technology characteristics had an interactive effect on TTM- “Too Little”, TTM, and TTM- “Too Much”. Hair et al. (2017) described the moderating effect as a “situation in which the relationship between two constructs is not constant but dependent on value of a third variable”. They explained that the moderating variable changes the strength of the direction of the relationship between the two constructs.

Hair et al. (2017) explained that with mediated moderation, the mediator variable intervenes with a moderating effect. The change in the interactive term results in a change in the mediator variable in the moderation model. While this would be an interesting consideration in the context of the present study, Hair et al. (2017) quoted Hayes (2013) who emphasised that no explicit testing of mediated moderation should occur as the analysis does not provide any data that impacts the results of the path model effects. They also argued that mediated moderation is challenging, and it may be impossible to establish theoretical/conceptual reasoning behind it. The researcher agrees with Hair et al. (2017) and Hayes (2013) who suggested that mediated moderation should be disregarded and for this reason this was not considered in this study.

#### ***Coefficient of determination ( $R^2$ Value)***

Hair et al. (2017) explained that the coefficient of determination ( $R^2$ ) enables researchers to “measure the model’s predictive power and is calculated as the squared correlations between a specific endogenous construct’s actual predicted values”. According to Harborth and Pape (2020), who quoted Hair et al. (2006), the  $R^2$  of the structural equations for the dependent variables provide an estimation of variance and explain how well the model can explain the dependent variables. They represent the exogenous latent variable combined effect on the endogenous latent variable. The  $R^2$  values for the study are listed in Table 5.10 below.

**Table 5.10: Coefficient of determination (R<sup>2</sup> Value)**

<b>Construct</b>	<b>R Square</b>	<b>R Square Adjusted</b>
Performance output	0.518	0.484
Task-technology fit (TTF)	0.438	0.422
Task-technology misfit (TTM) – "Too Much"	0.227	0.204
Task-technology misfit (TTM) – "Too Little"	0.225	0.202
Underground miner reactions	0.357	0.339
Utilization	0.629	0.618

As can be seen, the R<sup>2</sup> value ranges from 0 to 1. Hair et al. (2017) stated that it is difficult to provide the rule of thumb for R<sup>2</sup> values as they depend on the complexity and research disciplines. In the present study, R<sup>2</sup> values are above 0.20 which are high in some disciplines, as Hair et al. (2017) argued. As observed in the study, other factors exist because of the increase in R<sup>2</sup>. These include many paths from the construct. The adjusted coefficient of determination (R<sup>2</sup> Adjusted) assists in understanding models with different exogenous constructs. The adjusted R<sup>2</sup> is 0.484 for performance outputs and 0.422 for TTF. Therefore, the model explains 48.4% of the variance of performance outputs and 42.2% of TTF. Further, it can be seen from Table 5.10, that the adjusted R<sup>2</sup> is 0.204 for TTM – "Too Much", 0.202 for TTM – "Too Little", 0.339 for underground miner reactions and 0.618 for utilisation. Based on these adjusted R<sup>2</sup> values, it can be deduced that explanatory variance of the model is 20.4% for TTM – "Too Much", 20.2% for TTM – "Too Little", 33.9% for underground miner reactions and 61.8% for utilisation. Harborth and Pape (2020) said these values can be interpreted differently. They suggested using a very conservative threshold as proposed by Hair et al. (2011), where R<sup>2</sup> values are weak with values around 0.25, moderate with values around 0.50 and substantial with values of 0.75. Thus, when using this classification as a reference point, the R<sup>2</sup> values for underground miner reactions are very weak. The TTM – "Too Much" and TTM – "Too Little" are weak to moderate. Performance output and utilisation are moderate to substantial.

### ***Effect size of f<sup>2</sup>***

Hair et al. (2017) explain the f<sup>2</sup> as a measure that allows for understanding the change in the R<sup>2</sup> when a specific exogenous construct is omitted from the model, thus allowing for evaluations of whether the omitted constructs have a substantial impact on the endogenous construct. This allows for assessing an exogenous construct contribution to an endogenous latent variable R<sup>2</sup> value. For this study, Table 5.11 below shows f<sup>2</sup>

**Table 5.11:  $f^2$  values evaluation**

<b>Construct</b>	<b>Performance output</b>	<b>TTF</b>	<b>TTM – "Too Much"</b>	<b>TTM – "Too Little"</b>	<b>Underground miner reactions</b>	<b>Utilisation</b>
Mobile technology characteristics		<i>0.472</i>	<b>0.219</b>	<b>0.186</b>		
Performance output						
SIC task mobile TTF		0.01				
SIC task characteristics		0.008		0.004		
SIC task mobile TTM – "Too Much"			0.002			
SIC task mobile TTM – "Too Little"				0.029		
TTF utilisation perform	0.044					
TTM Much utilization perform	0.005					
TTM – "Too Small" utilisation perform	0.011					
Task-technology fit (TTF)	0.133				<b>0.219</b>	<b><i>0.736</i></b>
Task-technology misfit (TTM) – "Too Much"	0.012				0.009	0.029
Task-technology misfit (TTM) – "Too Little"	0.034				0.029	0.006
Underground miner reactions						
Utilisation	0.112					

Harborth and Pape (2020) quoted Cohen (1988) stating that to assess the threshold of the values, define effects as small, medium, and large for values of 0.02, 0.15, and 0.35, respectively. Table 5.11 shows that the values in italics indicate small effects, values in bold indicate medium effects, and values in bold and italics indicate large effects. All other values have no substantial effect. The results correspond with those of the previous analysis of the path coefficients.

### ***Blindfolding and predictive relevance of $Q^2$***

Hair et al. (2017) advised that researchers should use the Stone Geisser  $Q^2$  value to evaluate predictive accuracy. Harborth and Pape (2020) defined  $Q^2$  as a measure that indicates the out-of-sample predictive relevance of the structural model regarding the endogenous latent variables based on a blindfolding procedure. Hair et al. (2017) explained that the PLS path model exhibits predictive relevance by accurately predicting data not used in the model estimations. They explain that  $Q^2$  value is obtained by blindfolding procedure which involves “a sample technique that omits every  $d$ th data point in endogenous construct indicators and estimates parameters with new data points”. In this study, the researcher followed the approach used by Harborth and Pape (2020) who suggested an omission distance  $d=7$ . Harborth and Pape (2020) also used the recommended values for  $d$  that are between five and ten, as suggested by Hair et al. (2011). Hair et al. (2017) argued that  $Q^2$  values larger than 0 for a specific reflective endogenous latent variable indicate the path model has predictive relevance for a particular dependent construct. Based on Harborth and Pape (2020), this study calculated the  $Q^2$  values using the cross-validated redundancy approach, since this approach is based on both the results of the measurement model and of the structural model.

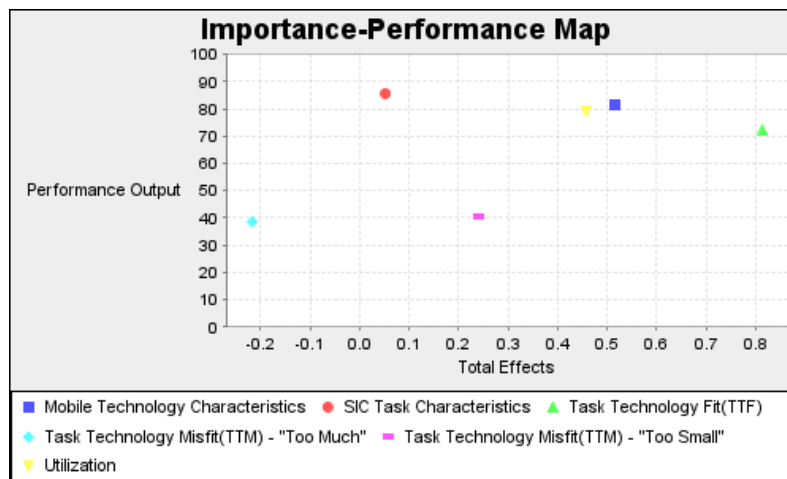
### ***Effect size of $q^2$***

Hair et al. (2017) stated that  $q^2$  effective size enables assuming the relative impact of predicting relevance, thus assessing an exogenous construct’s contribution to an endogenous latent variable’s  $Q^2$  value. As a comparable measure of predictive relevance, the  $q^2$  values of 0.02, 0.15 and 0.35 are small, medium, and large respectively. Harborth and Pape (2020) stated that the assessment of  $q^2$  follows the same process as  $f^2$ . They added that it is based on the  $Q^2$  values of the endogenous variables and calculates the individual predictive power of the exogenous variables by omitting them and comparing the change in  $Q^2$  (Hair et al., 2017). All individual values for  $q^2$  are calculated with an omission distance  $d$  of seven.

### **5.4 Importance-performance map analysis (IPMA)**

Hair et al. (2017) reported that IPMA “extends PLS-SEM results reporting of path coefficients estimates by adding a dimension to the analysis that considers values of the latent score”. They explained that IMPS relies on total effects and rescaling of latent variable scores to facilitate comparison of latent variables measured on a different scale. This study conducted the IPMA. When running the IPMA, the maximum iteration was set to 300 and stop creation 10 to 7. The

target construct was performance outputs, and the IPMA results obtained were for all predecessors of the selected target construct.



**Figure 5.2: IPM for constructs and standardised effects**

Task-technology fit, mobile technology characteristics, and utilisation are high on the right-hand area of the importance-performance map and have high importance for the performance output and high total effects; thus, they might increase performance output performance.

### 5.5 Statistical power analysis

Statistical power analysis aids in determining the appropriate sample size for analysis as well as determining whether the model is robust enough to detect real-world significant effects. When analysing a link between two variables, Sawyer and Ball (1981) indicated that researchers typically presume that a relationship exists. However, it is possible that some relationships may not exist. It is for this reason that the null hypothesis, according to Sawyer and Ball (1981), is set to reject it if there is a relationship. However, sometimes a Type II error might happen where a statistical test incorrectly fails to reject a null hypothesis (Sawyer & Ball, 1981). According to Sawyer and Ball (1981), "If 1 refers to the probability of a Type II error, then power is  $1 - P$ ". Thus, statistical power, according to Sawyer and Ball (1981), is the "probability that a statistical test would correctly reject a null hypothesis". The significance threshold, the precision of sample estimates, and the effect size are used to assess statistical power, they say. The "significance criterion comprises the chosen Type I error rate (the probability of incorrectly rejecting a null hypothesis) and whether a directional (one-tailed) test is employed", according to Sawyer and Ball (1981). When Type I error rates are higher and

directional hypotheses are used, power increases. Sawyer and Ball (1981) explained that the sample size is the most important factor in determining the precision of sample estimates; bigger samples have more statistical power. The amount or strength of a relationship between two or more variables in a population is referred to as the effect size. The larger the impact size, the greater the power, if other design elements are kept constant. In the early stages of a research design, the effect size should be the most important factor to consider. However, because it is more complex to calculate than significant criteria or sample size, the impact size is probably less frequently openly evaluated by many researchers. Sawyer and Ball (1981) cite Cohen (1977) who indicated that effect size can be explained in terms of proportion of explained variance.

According to Cohen (1977), the difference between two means for a t-test can be written as  $d$ , the standardised difference, or in terms of a point-biserial correlation, as Sawyer and Ball (1981) suggested. Cohen (1977) proposed that  $d$  values of .20, .50, and .80 represent small, medium, and large impact sizes, respectively. These figures equate to explained variance proportions of 1%, 5.9%, and 13%, respectively, as defined by the point-biserial correlation coefficient. According to Sawyer and Ball (1981), assessing impact magnitude prior to empirical investigation might be difficult. Alternatives include making estimations based on similar study findings or doing a pretest to assess effect size. According to Sawyer and Ball (1981), numerous academics argue for a power effect of 80% or 0.8 if the Type I error rate is 5% or 0.05.

Priori power analysis and post hoc power analysis are the two main methods of power analysis. A one-tailed t-test study uses A - priori power analysis to compute the minimum required total sample size per-group. This type of power analysis can be done with the G\*Power 3 software (Faul et al., 2007). In this case, the probability level, also known as Type I error or p-value, can be set to 0.05, with an observed effect size (Cohen's  $d$ ) of 0.5 and a desired statistical power of 0.8. This results in a required minimum total sample size (one-tailed hypothesis), which is usually 104. A priori power analysis was not performed in the present study. To ensure that the sample size was comfortable, the researcher used Hair et al.'s (2017) proposed sample size rule of thumb. Furthermore, as many researchers have noted, the choice of PLS-SEM was predicated on its ability to manage small sample numbers (Hair et al., 2017).

Many relationships were tested in this study, resulting in a complex model. Furthermore, some correlations were discovered to be non-significant when they were predicted to be significant

according to the theory on which the hypothesis was founded. A post hoc power analysis was conducted using the G\*Power 3 software to see if the non-significant results were due to a lack of statistical power (Faul et al., 2007). When the results suggest that some paths are significant, but they are not meant to be significant, post hoc power analysis is used. A post hoc power analysis is required for those pathways. The post hoc power analysis, the probability level or Type I error or p-value set at 0.05, effect size (Cohen's  $d$ ) of 0.8, which is large, and sample size of 106 and two-tailed were investigated in the current study. The post hoc power analysis was performed on endogenous variables to check for power effects in specific associations. The observed power (one-tailed hypothesis) was above 0.8. This indicated that the sample size of 106 was sufficient for statistical significance at the .05 level. As indicated earlier, Gefen et al. (2000) recommended that the minimum sample size required should be "10 times the number of items in the most complex construct". In the model for this study, the complex model comprised mobile characteristics which have 10 items and thus the minimum sample size would have been 100 participants. The realised sample in this study was 106, which is above the minimum, hence meeting the requirement recommended by Gefen et al. (2000). As a result, the unfavourable results cannot be attributed to a small sample size.

## **5.6 Chapter conclusion**

This chapter provided a detailed explanation of the data analysis techniques, procedures, and software used in analysing the data and making conclusions based on the model provided. The chapter further discussed how these would be presented rigorously, including the testing for validation and reliability to be performed.

## CHAPTER 6: RESEARCH DISCUSSIONS

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### 6.1 Introduction

The previous chapter presented the findings of the research data analysis. The present study investigated the task–technology fit/misfit (TTF/M) role as a mediator between the interactive effect of short interval control and mobile technology characteristics. Specifically, the study addressed how TTF and TTM of mobile-enabled short interval control systems impact performance outcomes of miners in an underground mine. As proposed, TTF and TTM were found to play an important role in the utilisation of mobile technology and facilitating how the underground miner reactions would be and their performance outcomes. All analyses controlled for age, education, experience, technology competence, and gender. Each of the TTF/M constructs had different mediating roles to utilisation, underground miner reaction, and performance outcomes. The new TTF/M model proposed by Howard and Rose (2019) was used as the framework of analysis for the study, and support was found for the usefulness of the model in the underground mining context. As explained earlier, the relationships between the constructs are discussed following the recommendation by Hair et al. (2017), who explained that the path coefficients close to +1 represent a strong positive relationship and those close to -1 represent a strong negative relationship. The closer the estimated coefficients are to 0, the better the relationships are. The path significance is at the 0.05 alpha level ( $p < 0.05$ ). This chapter discusses the findings in reference to the main research hypotheses.

### 6.2 Discussion of findings or results

#### 6.2.1 Influence of underground short interval task characteristics on TTM/F

The relationships between the direct effect of SIC task characteristics on TTF, TTM – "Too Much" and TTM – "Too Little" were not significant. More specifically, underground short interval control task characteristics did not positively influence TTM – "Too Much" ( $B = -0.087$ ,  $p > 0.05$ ), thus invalidating H1a. Furthermore, H1b was invalidated with underground short interval control task characteristics and did not positively influence task-technology fit (TTF) ( $B = 0.098$ ,  $p > 0.05$ ). Underground short interval control task characteristics did not positively influence TTM – "Too Much" ( $B = 0.029$ ,  $p > 0.05$ ), thus invalidating H1c.

Prior research did not investigate the direct relationship between technology characteristics and task characteristics on TTM – “Too Little” and TTM – “Too Much”. It is for this reason that Howard and Rose (2019) introduced the concept of TTF – “Too Little” and TTM – “Too Much” as part of better operationalisation of the TTF model.

More studies have been conducted regarding task-technology characteristics and their direct effects on TTF (Gebauer & Tang, 2008; Strong et al., 2006). The current study results suggest that short interval task characteristics that are not adequately developed do not create a better fit for underground miners to perform their tasks. Further, even well-developed SIC task characteristics alone do not positively influence TTF in underground mining environments. The same can be said for SIC task characteristics that are too highly developed and sophisticated for the miners.

### **6.2.2 Influence of mobile technology characteristics on TTM/F**

The relationships between the direct effect of mobile technology on TTF ( $B = 0.635, p < 0.05$ ), TTM – “Too Much” ( $B = -0.507, p < 0.05$ ) and TTM – “Too Little” ( $B = -0.468, p < 0.05$ ) were significant. Therefore, the hypotheses H2a, H2b and H2c are validated. These findings on the relationship between mobile technology characteristics and TTF/M were consistent with previous TTF studies (Barki et al., 2007; Dishaw & Strong, 1999; Goodhue & Thompson, 1995; McGill & Klobas, 2009; Staples & Seddon, 2004). The present study suggests that mobile technology characteristics that are less (TTM – “Too Little”), fully (TTF) or over (TTM – “Too Much”) developed create a better fit for underground miners to perform their tasks.

### **6.2.3 Influence of the interactive effect of mobile technology and short interval control characteristics on TTM/F**

Howard and Rose (2019) argued for testing the interactive effect in TTF research and not only direct effects. In the present study, various relationships involving the interactions between mobile technology characteristics and SIC task characteristics and effect on TTM – “Too Little”, TTF and TTM – “Too Much” were tested. The test for interactive effects of SIC task and mobile technology characteristics was carried out using the moderating effect used in Smart PLS 3.3.3 (Ringle et al., 2015). The results of the interactive effects are presented in Table 5.7. The results showed that the interactions of SIC task and mobile technology characteristic in influencing TTM – “Too Little” ( $B = -0.123, p > 0.05$ ), TTF ( $B = 0.061, p > 0.05$ ), and TTM – “Too Much” ( $B = -0.032, p > 0.05$ ) were not significant. Therefore, the

hypotheses H3, H4 and H5 are invalidated. The result of the effect of interactions on TTF is not consistent with that of Howard and Rose (2019) who found that several task and technology characteristics have an interactive effect of producing TTF, but the relationships of these effects are nuanced. For instance, some characteristics had interactive effects that only predicted TTF, others only predicted TTM, and even others predicted both. This study focused on investigating this matter within context. In fact, Howard and Rose (2019) suggested that their results were not conclusive and needed further research to understand the effects. This research presented an opportunity to test these relationships.

#### **6.2.4 Influence of task-technology fit and task-technology misfit on utilisation**

Many IS researchers have discussed the role of TTF on utilisation decision (Nance & Straub, 1996; Ahluwalia, Gimpel & Varshney, 2015). In the present study, various relationships involving TTM – “Too Little”, TTF and TTM – “Too Much” and utilisation were tested. The relationship between TTM – “Too Little” and utilisation was not significant ( $B = 0.071$ ,  $p > 0.05$ ). This invalidated H6b. TTM – “Too Much” did not have a significant positive relationship with utilisation ( $B = -0.159$ ,  $p > 0.05$ ). This invalidated H8b. The results of the tests of relationships for TTM – “Too Little” were not consistent with the results of the work by Howard and Rose (2019) who found that TTM – “Too Little” had a negative, strong, and significant relationship with utilisation. However, the result of the tests of relationships for TTM – “Too Much” were consistent with the results of the work by Howard and Rose (2019) who found that TTM - “Too Much” had a negative, small, and nonsignificant relationship with utilisation. The other relationship tested was between TTF and utilisation and this was significant ( $B = 0.729$ ,  $p < 0.05$ ). This validated H7b. This result was consistent with the TPC model proposed by Goodhue and Thompson (1995) which found that TTF had a significant positive effect on utilisation. It is also consistent with Howard and Rose (2019) who found that TTF had a positive, strong, and significant relationship with utilisation.

#### **6.2.5 Influence of task-technology fit and task-technology misfit on underground miner reactions**

The relationships between TTM – “Too Little”, TTF and TTM – “Too Much” and underground miner reactions were tested. The relationship between TTM – “Too Little” and underground miner reaction was not significant ( $B = -0.207$ ,  $p > 0.05$ ). This invalidated H6a. TTM – “Too Much” did not have a significant relationship with underground miner reaction ( $B = 0.114$ ,  $p > 0.05$ ). This invalidated H8a. The results of the test of relationships for TTM – “Too Much”

were not consistent with the results from the work by Howard and Rose (2019), who found that TTF – “Too Much” had a negative, small, and nonsignificant relationships with user reactions. The results of the test of relationships for TTM – “Too Much” were consistent with the results from work by Howard and Rose (2019), who found that TTF – “Too Much” had a negative, small, and nonsignificant relationships with user reactions. The other relationship that was tested included TTF and underground miner reaction and this was significant ( $B = 0.523$ ,  $p < 0.05$ ). This validated H7a. This result was consistent with Howard and Rose (2019), who found that TTF had positive, strong, and significant relationships with user reactions.

### **6.2.6 Influence of task-technology fit and task-technology misfit on underground miner performance outcomes**

The relationships between TTM – “Too Little”, TTF and TTM – “Too Much” and underground miner performance were tested. The relationship between TTM – “Too Little” and underground miner performance was not significant. TTM – “Too Much” did not have a significant relationship with underground miner performance ( $B = -0.144$ ,  $p > 0.05$ ). This invalidated H8c. Furthermore, TTM – “Too Little” did not have a significant relationship with underground miner performance ( $B = 0.207$ ,  $p > 0.05$ ). This invalidated H6c. The results of the tests of relationships for TTM – “Too Little” were not consistent with the results from the work by Howard and Rose (2019) who found that TTM – “Too Little” had a negative, strong, and significant relationship with performance. However, the results of TTM – “Too Much” were consistent with results from the work by Howard and Rose (2019) who found that a negative, small, and nonsignificant relationships with performance. The other relationship tested included TTF and underground miner performance and this was significant ( $B = 0.482$ ,  $p > 0.05$ ). This validated H7c. This result was consistent with Howard and Rose (2019) who found that TTF had a positive, strong, and significant relationship with performance. It is also consistent with Goodhue and Thompson (1995) who asserted that there is a strong support for TTF as a predictor of performance impacts. Other IS studies also shows similar results where fit has a positive influence on performance (Staples & Seddon, 2004; Zigurs & Buckland, 1998).

### **6.2.7 Mediating role of utilisation between task-technology fit and task-technology misfit on underground miner performance outcomes**

Utilisation plays a significant role in the usage of the systems. The mediation role of utilisation has not been fully investigated (Goodhue & Thompson, 1995; Howard & Rose, 2019). As

explained earlier, mediation is calculated in the same way as the interaction term in Smart PLS 3.3.3 (Ringle et al., 2015). As also explained earlier, the testing of the interactive effect in TTF research has been heavily advocated for by Howard and Rose (2019). In this study, the relationships between TTM – “Too Little”, TTF and TTM – “Too Much” and underground miner performance mediated by utilisation were tested. The relationship between TTM – “Too Little” and underground miner performance mediated by utilisation was not significant ( $B = -0.113, p > 0.05$ ). This invalidated H9a. TTM – “Too Much”, mediated by utilisation did not have a significant relationship with underground miner performance ( $B = 0.096, p > 0.05$ ). This invalidated H9b. The other relationship tested included TTF and underground miner performance mediated by utilisation and this was significant ( $B = 0.183, p < 0.05$ ). This validated H9c.

### **6.2.8 Influence of utilisation on underground miner performance outcomes**

The relationship between utilisation and underground miner performance was tested and found to be significant ( $B = 0.457, p < 0.05$ ). This validated H9d. The results of the test of relationship were consistent with the results from the work by previous authors (Goodhue & Thompson, 1995; Howard & Rose, 2019) who found that utilisation has a significant relationship with performance.

### **6.3 Chapter conclusion**

This chapter has provided a detailed explanation of the data analysis techniques, procedures, and software used in analysing the data and making conclusions based on the model provided. The chapter further discussed how these were presented rigorously, including the testing for validation and reliability.

## **CHAPTER 7: MANAGERIAL RECOMMENDATIONS, IMPACTS AND THEORETICAL CONTRIBUTIONS**

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### **7.1 Chapter Introduction**

The chapter provides an outline of managerial recommendations and theoretical contributions of the present research. The managerial recommendations can play a key role in driving continuous improvement and bringing the next value addition to the practice of mobile-enabled short interval control systems.

### **7.2 Theoretical contributions**

This study contributes to theory testing and building and further improvement of scholarly understanding of the task technology fit model in different ways.

First, the study has extended the task technology fit model by applying it in a real world context and adding the variables for SIC user tasks executed in underground mining. Goodhue and Thompson (1995) called for more improvement to the TTF model by adding more user tasks. The tasks related to the SIC business process play a significant role in optimising the underground mining process and reducing waste. Thus, the value of SIC tasks in a specific business process context is that this allows for better understanding of the role of TTF theory to achieving digital transformation goals.

Secondly, Goodhue and Thompson (1995) called for more avenues for future research by expanding the scope of using TTF in more diverse settings and across different companies. The case study chosen for this research is a unique setting that facilitates the contribution to TTF theory. The case study provided a real-life context and applied the Howard and Rose (2019) framework. Specifically, this is the first time the Howard and Rose (2019) new TTF/M model was used within a mining industry context. The data from underground mining contributes to the study of task technology fit in a novel way. Using the hypotheses, both TTF and TTM have been evaluated and discussed. This is critical to the overall understanding and application of the TTF theory in various underground mining contexts.

Thirdly, the study design presented several advantages to the understanding of the constructs and their relationships. Many researchers have used the PLS-SEM approach when studying

and applying the TTF theory (D'Ambra et al, 2012; Tam & Oliveira, 2019). However, this study applied this data analysis approach within the context of underground mining. This is unique and enabled the researcher to understand the relationships better and test them, using a well-known process.

Fourth, the research model used in the study specifically for the SIC business process and mobile technology, though used in the underground gold mining context, can be used in other different underground mining contexts such as Copper, Coal, Iron etc. The research used the SIC business process and mobile technology characteristic scales that can be re-used in other mining contexts. For example, the SIC business process is based on the GMG (2019) underground SIC guideline which is not mineral specific. The scales for TTF/M are based on the scales proposed by Goodhue and Thompson (1995) and Howard and Rose (2019). This makes the study to be replicable in other underground mining contexts where SIC and mobile technology has been implemented.

Fifth, although TTF studies have been around for some time, few studies have investigated how utilisation moderates and mediates the relationship between TTF/M and performance (Howard and Rose, 2019). This study evaluated/tested the relationships between TTM – “Too Little”, TTF and TTM – “Too Much” and underground miner performance mediated by utilisation. Only the TTF and underground miner performance relationship mediated by utilisation was significant. In this study, it was found that TTF mediated by utilisation positively influences underground miner performance outcomes

### **7.3 Managerial recommendations**

This research provides specific insights that can improve practice. Specifically, the results suggest the mediating role of TTF/M in the interactive nature of SIC task characteristics and mobile technology and the impact on underground miner reaction, utilisation, and performance outcomes. This is fundamental to the understanding, implementation and ongoing support processes of successful mobile-enabled SIC systems. The results from the present research have several implications for Mining Underground Managers, Operational Excellence, Dispatch Specialists, and IT experts when faced with the possibility or mission of implementing and managing a successful mobile-enabled SIC system. The study provides a SIC TTF/M assessment tool that can enrich the SIC system's decision-making process. Therefore, to support the SIC development, implementation, and use process, the following recommendations are relevant.

### **Recommendation #1: Conduct off-the-shelf (commercial) vs. bespoke (custom) developed SIC applications decision analysis**

The research results raise exciting considerations that have been discussed intensely in the software acquisition literature. Many organisations debate whether they should buy off-the-shelf software or develop (internally or externally) custom applications based on their requirements. One of the things mostly criticised when doing in-house development is a front-loading software process. Colazo (2014) investigated the concept of lead user-driven innovation regarding software, and indicated that Hippel (1986) discussed user-aided innovation, where the development of new products with active help from users has continued to gain momentum in recent years. They tested whether front-loading the problem-solving process is associated with development performance. They found that front loading is associated with increased code quality but decreased development productivity. Over the years, the trend has shifted to where many companies are accepting more off-the-shelf applications. However, these applications have suffered lack of alignment to the organisation's specific business processes, which has resulted in systems that do not fully meet the expectations of the business. The mining industry has not been exempted from such challenges. Resistance to installing off-the-the-the-shelf software systems can be considerable.

The software purchase discussion has become critical in mining, as more companies continue to drive the digitisation of the operations in general and mining business processes such as SIC in particular. The evidence in the present study suggests that the interactions between SIC task characteristics and mobile technology characteristics mediated by task technology fit and moderated by utilisation have a significant effect on performance outputs. Therefore, the need to answer the software selection question (buy vs. build) has become very important.

As mining undergoes digital transformation and introduces new software systems that automate the tasks previously done manually, like SIC, it should be acknowledged beforehand that no automated system is a "Silver Bullet". As such, most automated systems will also have gaps (manual tasks vs. automated tasks). Thus, there should be a deliberate process to identify the gaps by using user evaluations adapted from the task technology fit framework. The data from the assessments should be analysed and used to identify fit and misfit areas, thus driving continuous improvement in the system. These continuous improvement initiatives should follow an automated change management process that applies some latest DevOps approaches (Development and Operations). Most miners might not be tech-savvy, thus any such

continuous development and continuous integration that are part of DevOps should be accompanied by effective communication and training. Training can occasionally negatively impact production output as the workforce is taken away from doing actual mining tasks. Thus, various learning approaches should be considered to facilitate knowledge transfer resulting from continuous digital short interval control system improvements.

While many mining companies are going back to having custom-developed applications, the researcher's viewpoint is that this is not sustainable and might result in high software maintenance costs. As such, mining companies considering digitising short interval control systems should consider configurable off-the-shelf SIC software with open architecture, application programmable interfaces (APIs) and meet minimum cyber security requirements. This will reduce software maintenance costs, minimise cyber risks and at the same time allow for easy customising of the system to a particular SIC business process for the specific mine. As part of the implementation process, resistance to use off-the-shelf applications may occur. Ilie and Turel (2020) examined user resistance to large systems. Their findings showed that while some influence tactics can help in reducing user resistance, others may backfire. They demonstrated that defiance, on the other hand, impels adaptive use of the system. Thus, Ilie and Turel (2020) believe that it is possible to control the resistances and adaptive behaviour with influence tactics, especially as many off-the-shelf artefacts can't be altered.

### **Recommendation #2: Data-driven value-based prioritisation of SIC feature enhancement**

In spite of successfully implementing off-the-shelf configurable SIC systems, the mining organisation's SIC business processes and software need to adjust quickly and rapidly to any new SIC requirements to stay agile. The software enhancement or improvement to custom-developed or bespoke software has been a practice problem for information systems practitioners for many years. This has become critical even with digital transformation, as many organisations in different industries, including mining, embrace digital software solutions. Because of the differences in business processes, the digital systems, once implemented, undergo many improvements. The software development processes have been enhanced by using the DevOps process, which facilitates continuous integration and continuous improvement. These processes have promoted agility and enabled rapid software improvement to meet changing business requirements using Agile project management and Scrum framework.

Therefore, the question is not whether the mining organisation should adapt the SIC software system and business process due to changing SIC requirements but how to perform value-based prioritisation around these requirements. This study has presented two exciting findings, which are being recommended as essential considerations for value-based prioritisation of SIC requirements. Firstly, the direct effect between SIC task characteristics and TTF, and mobile technology and TTF entails that both task characteristics or business process and mobile technology requirements should be identified and prioritised. These requirements proposed by the customer should not be based on 'gut feel' regarding how these will influence the TTF. They should be based on value proposition to the SIC process. Therefore, the survey tool used in this study can be helpful to guide the process by adjusting the new requirements as characteristics of any of the two constructs, namely SIC and mobile technology characteristics. This research has proposed that key end-users assess the proposed new requirements by completing the survey and providing feedback. The data would then be modelled to determine fit/misfit impacts and performance impacts. Secondly, the present study suggests that this quantitative TTF-based assessment process will enable value-based prioritisation decisions.

**Recommendation #3: Using the data-driven SIC TTF/M questionnaire as an assessment tool**

As discussed in the previous section, the identification and value prioritisation of requirements for change to software systems is a known industry issue. Many organisations build system enhancement lists and subject them to development based on individual suggestions or intuition. The present study proposes using the questionnaire as an assessment tool. The tool should be flexible and allow for updating SIC process characteristics and mobile technology enhancement. This will allow for data collection that should be assessed using the TTF/M process and modelled to understand the TTF/M as well as the impact on user reaction, utilisation, and performance outputs. Having such a tool will assist practitioners to better predict the effect of the change requests on performance output, utilisation, and user reaction and thus apply better values-based prioritisation decisions.

Another benefit offered by using the questionnaire is group decision-making because the main actors involved in using the system participate and provide input to the suggested feature change. This action happens from the beginning of the process and progresses throughout as the assessment occurs when it impacts on reactions, utilisation, and performance output. This approach enables better change management for new features, engages users in decision-

making early, promotes a group decision-making culture, and encourages using a theoretically grounded approach to understanding TTF/M.

#### **Recommendation #4: Applying an agile methodology to developing and deploying SIC changes**

Traditionally, waterfall project management has been the central approach for developing and deploying changes within the mining environment. This is because mines' business processes are heavily structured, and thus, the waterfall has been a good fit. A cultural shift needs to happen within the mining companies' business processes to encourage agility and rapid responses to high-value changes. This agile mindset needs to be driven by senior management and applied to the development and continuous improvement of various business processes.

Specifically, the researcher recommends the use of Scrum, which is a well-known Agile framework. As per the practice of Scrum, the new requirements for change, once identified using value-based prioritisation, need to be added to the prioritised backlog. These will be groomed further and added to the next sprint to be worked on either by local or offshore SIC development teams. The various Scrum ceremonies such as daily stand-up, backlog grooming, Sprint review and Sprint retrospective will occur until the new feature is released to the end-users. Effective communication regarding these changes will result in better underground miner reactions.

#### **Recommendation #5: Collaboration technologies driving a decentralised approach to the SIC process**

As stated earlier, multiple technologies were used in SIC in the current study and these include fleet management system, collaboration technologies, scheduling apps, location tracking, etc. Traditionally, the SIC, which is heavily driven by the mining control room, has had a command-and-control structure. In such a structure, all the communication for coordinating mining activities goes through the central location, and the decisions are centralised regarding truck movement, reassignments, etc. The mining operator's role has been limited to receiving directives from the command centre and finding space to communicate back. Many central commands-driven SIC systems make intense use of radio systems which may become congested when working through the command control structure. These have advantages of creating a unified vision of the mission, communication, and coordinating the same message

across operating units in the field. The disadvantage is such a structure has a single point of failure. This might happen due to technical challenges at the central command, etc.

The introduction of collaboration technologies such as Cisco Webex Teams, which are used at TRUG, brings a dynamic change to the command-and-control structure concept. It decentralises communication and empowers the teams to effectively communicate from Radio system (one to one/one to many) to the Cisco Webex team Spaces chats (One to one, one to many, many to many). Thus, this presents significant opportunities for effective communication without relying on a third party.

#### **Recommendation #6: Implement a mobile device use policy**

Mining is a safety-sensitive industry, and there are safety concerns regarding allowing mobile devices to be with the operators. There is still an opportunity to use them safely without causing hazards. The researcher would argue that the same risks associated with the mobile device might happen to radio systems. Therefore, the mining companies using a mobile-enabled SIC solution should implement a mobile device use policy. As reviewed by the present study, mobile technology with SIC characteristics mediated by TTF/M impacts miner reaction. Thus, it is up to the individual operators to follow company-established mobile device use policies for mining and they should exercise good judgment when using the radio or mobile communication systems. Having a mobile policy and communicating it effectively to underground miners will potentially reduce mobile device-related incidents.

#### **Recommendation #7: Fit-driven SIC maturity modelling**

GMG (2019) has proposed a SIC maturity model for underground mines. The model is based on a previous maturity model, such as the capability maturity model. The maturity models are beneficial to ensure a business process and associated technologies have a roadmap and at any time can measure their successes or growth. As such, the researcher argues that the proposed SIC maturity model for underground by the GMG Group (2019) can be used as a starting framework for many mining companies. Obviously, further work needs to be done to develop measures that would allow for data collection to determine the organisation's level of maturity.

If a mining company uses the GMG Group (2019) maturity model, it will act as a catalyst for change or improvement to the SIC mobile technology features or business process characteristics. The researcher recommends using the TTF/M approach to test drive the readiness of underground miners before striving for the next level of maturity. Using this

approach might mean phrasing TTF/M survey questions in a futuristic or hypothetical state, allowing the respondent to know that this is implied for future changes.

### **Recommendation #8: Digital SIC user evaluation**

The study has concluded that user evaluations are essential to adapt the system to manual task characteristics. This is consistent with the Goodhue (1995) and Goodhue and Thompson (1995) study conclusions on IS evaluations. In this present study, user evaluations provided an opportunity to know what is working well (fit) and what needs improvement (misfit).

Many generic system evaluation tools have been developed over the years. This study has reviewed the specific context of short interval control systems using mobile technology. The mine leaders and teams leading implementations or managing such systems can use the digital SIC user evaluation tool that has been proposed in this study. The tool can be adapted to the specific needs of the mine. The tool has been created and made available as a template in SurveyMonkey, accessible by searching using the words "Digital SIC User Evaluation Tool".

## **7.4 DBA managerial impacts**

Kalika (2020) explained that one of the key distinguishing characteristics of a Doctor of Business Administration (DBA) is the managerial impacts on the researcher's personal and professional life, the academic community, the manager's organisation, and society. These impacts might arise because of the results that the manager - researcher has found during the four phases of the DBA research, namely when defining the DBA project, executing the project, dissemination of outcomes of the research, and practical implementation of the outcomes in the organisation (Kalika, 2020).

The purpose of the next section is to explain these impacts in the context of the present research.

### **7.4.1 Personal and professional life**

One of the significant personal impacts of the DBA research was strengthening the researcher's personal organisation skills regarding time management, prioritisation of work, and the discipline to focus on the set goals. Kalika (2020) correctly noted that the DBA candidate's ability to combine doctoral work with family and professional priorities is critical during the DBA journey. Due to various competing priorities, the researcher had to identify the best approach to develop the discipline over time. On some occasions, things fell through the cracks, and the researcher had to do course correction to remain on target. Kalika (2020) discussed the

motivations for many DBA applicants as being pride, pleasure, and fulfilment. These positively impacted the researcher's ability to remain focused during the execution of the DBA project.

On the professional side, the researcher was highly motivated to pursue the programme and got support from the employer to use the TRU as a case study. The previous postgraduate studies completed by the researcher were purely focused on research. This provided essential skills and high-level good research expectations. The university provided the researcher with access to world-class online libraries with the latest peer-reviewed articles from top information systems journals. Kalika (2020) summarised these factors needed to complete the DBA project as motivation, resources, and skills. These were helpful during the definition and execution of the DBA project and thus allowed the researcher access to empirically grounded research in the research focus area. This further allowed for having advanced conversations with other managers in the mining operations areas and resulted in having a mobile-based short interval control research project. The professional prospects of having a DBA impacted the researcher's ability to craft a research project that is relevant to the employer and industry in which they work. Kalika (2020) explained that the professional considerations for the DBA include competitive edge, career advancement, and legitimacy. These played a role during the decision to pursue a DBA and also when executing the project.

#### **7.4.2 Academic community**

Kalika (2020) noted that the DBA research can have an impact on the academic community. The researcher became a member of the Association of Information Systems (AIS). During the execution of the project, the researcher had interactions with various members of the information systems academic community. The researcher presented the research in progress at an Information Systems seminar hosted by the Department of Information Systems at the University of Nevada, Reno. Further, the Business Science Institute follow-up presentations were great sources of feedback on the project. This feedback helped refine the project and led to further reading. The researcher had new network contacts in the IS community who have become a valuable source of mentorship with the potential to conduct some projects and publish papers jointly. The researcher intends to publish research papers from the DBA research project in IS or management science journals.

### 7.4.3 Researcher's organisation

The DBA project had an impact on the researcher's organisation. Kalika (2020) explained that during the DBA project definition, there are interactions between the DBA project researcher and other managers. As discussed earlier, this was the case for this project. The researcher worked at the TRU as an IT Manager and thus had approved access to different resources and personnel who enormously impacted the researcher's understanding of the SIC mining business process and shaping of the research project. During the execution of the project, the researcher's knowledge of the role of fit between technology and task characteristics, including how this impacts performance, resulted in the adoption of agile project methodology, specifically Scrum. This was implemented as part of managing SIC enhancements and resulted in lessons learned on the use of Scrum in the mining context. The researcher had to learn and get certified as a Scrum master and be a change driver within the IT and operational departments. The result was better backlog management, prioritisation, and cost reduction.

### 7.4.4 Other organisations

While the research project did not significantly impact other organisations, it is essential to note that the researcher joined the Global Mining Guidelines group, which has authored a critical white paper on underground short interval control. This paper became a significant source of insight for the project. The researcher's participation in this group's activities enabled them to better understand SIC and its future.

Table 7.1 shows a summary of research results, recommendations, impacts, prioritisation, and feasibility as adapted from the proposed approach to presenting managerial impacts by Kalika (2020). Use the key below:

*Feasibility category* => \*: very low; \*\*: moderate; \*\*\*: very high

*Players* => MC: Manager-Candidate; M: Other managers; C: Company; S: Dispatch or Fleet management specialists; IT: IT Specialists

*Recommendations classified by urgency and importance as per Eisenhower matrix* => L: Low; M: Moderate; H: Higher; VH: Very high

**Table 7.1: Summary of research results, recommendations, impacts, prioritisation, and feasibility**

Recommendation	DBA thesis result	Players	Priority in terms of urgency	Priority in terms of importance	Feasibility			
					Financial	Technical	Organisation	Support from players
Recommendation # 1	Direct effect of mobile technology on TTF, TTM – "Too Much" and TTM – "Too Little" was significant	<i>MC, M, C, S, IT</i>	L	VH	***	***	***	***
Recommendation # 2	Direct effect of mobile technology on TTF, TTM – "Too Much" and TTM – "Too Little" was significant	<i>MC, M, S, IT</i>	VH	VH	**	**	*	*
Recommendation # 3	Relationship between TTF and underground miner performance was significant	<i>MC, M, S, IT</i>	L	M	***	***	*	*
Recommendation # 4	The relationship between utilisation and underground miner performance was tested and found to be significant	<i>MC, M, C, S, IT</i>	H	H	***	**	**	*
Recommendation # 5	The relationship between TTF and underground miner reaction was significant	<i>MC, M, C, S, IT</i>	H	VH	***	***	***	***
Recommendation # 6	The relationship between TTF and underground miner reaction was significant	<i>MC, M, C, S, IT</i>	VH	VH	***	***	***	***
Recommendation # 7	Relationship between TTF and underground miner performance was significant	<i>MC, M, C, S, IT</i>	VH	VH	***	**	*	**
Recommendation # 8	Direct effect of mobile technology on TTF, TTM – "Too Much" and TTM – "Too Little" was significant	<i>MC, M, C, S, IT</i>	M	M	***	**	*	**

## **7.5 Chapter conclusion**

The study was conducted using one case study of the Turquoise Ridge underground gold mining using the quantitative methodology. The present study makes recommendations to bring about organisational changes. These changes would encompass SIC procedures, methods, and behaviours. From the onset, the results related to task technology misfit will drive change management and specific continuous improvement in making the SIC software applications align or suitable to the tasks. The performance scorecard related to the use of the system will be promoted to evaluate the performance of TTF/M and attainment of key performance indicators by the individuals.

## CHAPTER 8: CONCLUSIONS AND FUTURE RESEARCH

### 8.1 Conclusions

The main goal of this study was to answer the following research question: “*What are the implications of short interval control tasks fit and misfit with mobile technology applications used by operational level miners in an underground gold mine?*” At the end of this thesis, the implications of Task Technology Fit (TTF) are that it results in better prediction, thus allowing for better decision making around improving the SIC process, which results in better performance of underground miners. However, Task Technology Misfit (TTM) implies that it is unpredictable and therefore makes it challenging to make decisions on improvement, thus negatively impacting performance. In addition, we can assess the difference between fit and misfit in terms of capability of performance prediction.

The application of the new TTF theory by Howard and Rose (2019) suggests that TTF is still a relevant mediating variable between task characteristics and technology characteristics in predicting performance outcomes, utilisation, and user reaction. The prediction of TTF on performance outcomes and user reaction is moderated by utilisation. And utilization predicts performance outcomes. This is consistent with the results from Goodhue and Thompson (1995) and other applications of TTF in different industries. Howard and Rose (2019) suggested that the TTM is not the opposite of TTF and should be conceptualised and operationalised differently. The present study has contributed to the understanding of the new TTF theory by assessing the different relationships between the individual and interaction of the constructs, SIC task characteristics, and mobile technology on TTF, TTM – “Too Little” and TTM – “Too Much”. By adapting the model proposed by Howard and Rose (2019), the researcher shows an interesting relationship between the TTF/M constructs and performance outcomes.

Further, the study's findings so far, based on a literature review, are not unique to mining. Most of the mobile-based applications deployed in different contexts have customisations to achieve better TTF. Thus, there is no “silver bullet” software that achieves TTF at once. The process of attaining TTF is a continuous learning journey that an organisation should embark on. Using suitable project management approaches such as Agile can deliver better value and benefit realisation. Finally, the study has concluded that user evaluations are important to adapt the system to manual task characteristics. They provide an opportunity to know what is working well (fit) and what needs improvement (misfit).

## **8.2 Limitations of the present research**

This research had limitations which are noted in this section of the thesis. Firstly, time was limited to comprehensively perform data collection as the target sample group or population were busy with their day jobs, they worked different shifts, and Covid-19 impacted personnel availability. For these reasons, only a sample of 106 employees formed part of the study. Despite the sample being 106 for an SEM model and some correlations discovered to be non-significant when they were predicted to be significant, a post hoc power analysis was conducted using the G\*Power 3 software to see if the non-significant results were due to a lack of statistical power (Faul et al., 2007). The probability level or Type I error or p-value was set at 0.05, effect size (Cohen'd) of 0.8, which is large, and sample size of 106 and two-tailed were investigated in the current study. The observed power (one-tailed hypothesis) for non-significant was more than 0.8. This indicated that the sample size was sufficient for statistical significance at the 0.05 level. Further, Gefen et al. (2000) recommended that when using partial least squares (PLS), the minimum sample size required should be "10 times the number of items in the most complex construct". In the model for this study, the complex model comprised mobile characteristics with 10 items and thus the minimum sample size would be 100 participants. The realised sample in this study was 106 which is above the minimum, hence meeting the requirement recommended by Gefen et al. (2000). Thus, the non-significance is not as a result of the sample size. Secondly, the questionnaire used in the study has been recommended as a tool for data-driven value-based prioritisation of SIC requirements. This questionnaire needs further development and testing in different SIC underground environments to validate its applicability, enhance its use, and allow for its customisation to meet specific requirements for change. Thirdly, the research was conducted using one case study in an underground gold mine. To better understand the application of TTF/M to different underground mining environments with different methods, more replication of the study in other contexts is needed. Fourth, the researcher was involved in supporting the digital SIC, and it might generate potential bias concerning respondents. The approach to deal with this limitation rigorously and ethically was addressed in Chapter 4 of this thesis. Lastly, as asserted by Rai and Selnes (2019), a study limitation was that the independent variables related to task-technology fit were not systematically manipulated in an experimental design.

### **8.3 Future research directions**

The present study conducted the TTF/M research in an underground mining context. Future research should investigate replicating the study in other underground and open cast mining environments where different metals such as coal, silver and copper are mined. There are many different mining methods and operational processes that might influence mobile-enabled SIC impacts on TTF/M and performance outputs. Future research should consider these factors. A second additional research stream to be investigated in the future is the consideration of using various research methodologies such as qualitative or mixed methods. A third proposed research direction should consider assessing TTF and TTM on a continuum. A fourth future consideration consists of improving the SIC mobile technology survey as an assessment tool as this has the potential to use customisation requirements and to enhance TTF. Fifth, most studies on TTF have focused on individuals as units of analysis. Future research should consider focusing on crews (team), group support systems, etc. as units of analysis resulting in a multi-level approach to TTF studies. This might entail using a different TTF theory for teams, such as the TTF theory proposed by Zigurs and Buckland (1998). Finally, the study can also be conducted with modifications to theoretical constructs by introducing different variables or combining the task technology fit model with other models such as the strategic alignment model or technology acceptance model and applying this to the unique context of mining.

## BIBLIOGRAPHY

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- Abdillah, W. & Saepullah, A., 2018. Model Technology to Performance Chain (TPC) in implementing accrual-based Sistem Informasi Manajemen Daerah (SIMDA) Finance: Empirical evidence from local government of Indonesia. *Jurnal Dinamika Manajemen*, 9, 56–68. [Online] Available at: <https://doi.org/10.15294/jdm.v9i1.14652> [Accessed 2 November 2020].
- Ahluwalia, P., Gimpel, G. & Varshney, U., 2015. A consumption theory and task-fitness perspective of wireless internet adoption for mobile commerce. *International Journal of Electronic Business*, 12(1), 46–69.
- Aljukhadar, M., Senecal, S. & Nantel, J., 2014. Is more always better? Investigating the task-technology fit theory in an online user context. *Information & Management*, 51(4), 391–397.
- Arksey, H. & O'Malley, L. 2005. Scoping studies: Towards a methodological framework. *International Journal of Social Research Methodology*, 8, 19–32.
- Bagozzi, R., Yi, Y. & Phillips, L., 1991. Assessing construct validity in organizational research. *Administrative Science Quarterly*, 36(3), 421–458.
- Barki, H., Titah, R. & Boffo, C., 2007. System use-related activity: A behavioral conceptualization of expanded information system use. *Information Systems Research*, 18, 173–192.
- Barrick, 2019. Underground mining breaks records as Kibali continues to deliver. *Globe Newswire*, 23 October. [Online] Available at: <http://www.globenewswire.com/en/news-release/2019/10/23/1934274/0/en/Underground-Mining-Breaks-Records-as-Kibali-Continues-to-Deliver.html> [Accessed 23 November 2020].
- Batterham, R., 2017. The mine of the future – Even more sustainable. *Minerals Engineering*, 107, 2–7.
- Bentler, P. & Bonett, D., 1980. Significance tests and goodness of fit in the analysis of covariance structures. *Psychological Bulletin*, 88(3), 588–606.
- Bentler, P. & Huang, W., 2014. On components, latent variables, pls and simple methods: Reactions to Rigdon's rethinking of PLS. *Long Range Planning*, 47(3), 138-145.
- Berthon, P., Pitt, L., Ewing, M. & Carr, C.L., 2002. Potential research space in MIS: A framework for envisioning and evaluating research replication, extension, and generation.

*Information Systems Research*, 13, 416–427. [Online] Available at: <https://doi.org/10.1287/isre.13.4.416.71> [Accessed 3 November 2020].

Bhattacharjee, A., 2012. *Social science research: Principles, methods, and practices*. United States: CreateSpace.

Bhattacharjee, A., Davis, C., Hikmet, N. & Kayhan, V., 2008. *User reactions to information technology: Evidence from the healthcare sector*. Proceedings of the International Conference on Information Systems (ICIS), Paris, France, December 14–17. [Online] Available at: <https://aisel.aisnet.org/icis2008/211> [Accessed 25 November 2020].

Blaikie, N.W.H. 2009. *Designing social research: the logic of anticipation*. Cambridge, UK: Polity Press. [Online] Available at: <http://books.google.com/books?id=pMZWAAAAYAAJ> [Accessed 2 November 2020].

Boote, D.N. & Beile, P., 2005. Scholars before researchers: On the centrality of the dissertation literature review in research preparation. *Educational Researcher*, 34, 3–15. [Online] Available at: <https://doi.org/10.3102/0013189x034006003> [Accessed 1 November 2020].

Cane, S. & McCarthy, R., 2009. Analyzing the factors that affect information systems use: A task technology fit meta-analysis. *Journal of Computer Information Systems*, 50, 108–123.

Carnap, R., 1962. *Logical foundations of probability*. Chicago: University of Chicago Press.

Chen, B., Wan, J., Shu, L., Li, P., Mukherjee, M. & Yin, B., 2018. Smart factory of Industry 4.0: Key technologies, application case, and challenges. *IEEE Access*, 6, 6505–6519.

Chevalier, F., Cloutier, L.M. & Mitev, N., 2019. *Research methods for the DBA*. France: Éditions EMS.

Chin, W. & Newsted, P., 2021. Structural equation modeling analysis with small samples using partial least squares. In R. Hoyle (ed.), *Statistical strategies for small sample research* (pp. 307–341). Thousand Oaks: CA: Sage Publications.

CISCO, 2017. *Barrick digs deeper into data for safety and productivity*. Barrick Gold Corporation Case Study. Toronto Canada: Barrick Gold Corporation. [Online] Available at: [https://www.cisco.com/c/dam/en\\_us/about/case-studies-customer-success-stories/barrick-case-study.pdf](https://www.cisco.com/c/dam/en_us/about/case-studies-customer-success-stories/barrick-case-study.pdf) [Accessed 2 November 2020].

Cohen, J., 1977. *Statistical power analysis for the behavioral sciences*. New York: Academic Press.

- Cohen, J., 1988. *Statistical power analysis for the behavioral sciences*. Hillsdale, NJ: L. Erlbaum Associates.
- Colazo, J., 2014. Performance implications of stage-wise lead user participation in software development problem solving. *Decision Support Systems*, 67, 100–108. [Online] Available at: <https://doi.org/10.1016/j.dss.2014.08.007> [Accessed 12 November 2020].
- Culot, G., Orzes, G., Sartor, M. & Nassimbeni, G., 2020. The future of manufacturing: A Delphi-based scenario analysis on Industry 4.0. *Technological Forecasting and Social Change*, 157, 120092. [Online] Available at: <https://www.sciencedirect.com/science/article/abs/pii/S0040162520309185> [Accessed 2 November 2020].
- D'Ambra, J., Wilson, C.S. & Akter, S., 2012. Application of the task-technology fit model to structure and evaluate the adoption of e-books by academics. *Journal of the American Society for Information Science and Technology*, 64, 48–64. <https://doi.org/10.1002/asi.22757> [Accessed 15 November 2020].
- Dare-Abel, O.A., 2014. Task-technology fit of CAD deployment in architectural firms in Nigeria. *International Journal of Engineering Research*, 3, 697–699. [Online] Available at: <https://doi.org/10.17950/ijer/v3s11/1115> [Accessed 16 November 2020].
- Davis, F.D., Bagozzi, R.P. & Warshaw, P.R., 1989. User acceptance of computer technology: A comparison of two theoretical models. *Management Science*, 35, 982–1003. [Online] Available at: <https://doi.org/10.1287/mnsc.35.8.982> [Accessed 18 November 2020].
- DeLone, W.H. & McLean, E.R., 1992. Information systems success: The quest for the dependent variable. *Information Systems Research*, 3, 60–95. [Online] Available at: <https://doi.org/10.1287/isre.3.1.60> [Accessed 23 November 2020].
- Dickson, G., DeSanctis, G. & McBride, D., 1986. Understanding the effectiveness of computer graphics for decision support: A cumulative experimental approach. *Communications of the ACM*, 29(1), 40–47.
- Dijkstra, T., 2014. PLS' Janus Face – Response to Professor Rigdon's 'rethinking partial least squares modeling: In praise of simple methods'. *Long Range Planning*, 47(3), 146-153.
- Dijkstra, T. & Henseler, J., 2015a. Consistent and asymptotically normal PLS estimators for linear structural equations. *Computational Statistics & Data Analysis*, 81(1), 10-23.
- Dijkstra, T. & Henseler, J., 2015b. Consistent partial least squares path modeling. *MIS Quarterly*, 39(2), 297-316.

- Dishaw, M.T. & Strong, D.M., 1999. Extending the technology acceptance model with task technology fit constructs. *Information & Management*, 36, 9–21. [Online] Available at: [https://doi.org/10.1016/s0378-7206\(98\)00101-3](https://doi.org/10.1016/s0378-7206(98)00101-3) [Accessed 12 November 2020].
- Ditton, E. & Beer, A., 2018. *IDC & ABB future of mining webinar*. [Online] Available at: [https://software.response.e.abb.com/IDCABBFutureofMiningwebinar?utm\\_campaign=2018Q4DisplayAds&utm\\_medium=advertisement&utm\\_source=Aspermont%20Australia%27s%20Mining%20Monthly&utm\\_content=Webinar](https://software.response.e.abb.com/IDCABBFutureofMiningwebinar?utm_campaign=2018Q4DisplayAds&utm_medium=advertisement&utm_source=Aspermont%20Australia%27s%20Mining%20Monthly&utm_content=Webinar) [Accessed 24 November 2019].
- Drazin, R. & De Ven, A.H.V., 1985. Alternative forms of fit in contingency theory. *Administrative Science Quarterly*, 30, 514. [Online] Available at: <https://doi.org/10.2307/2392695> [Accessed 23 November 2020].
- Ericsson, M. & Löf, O., 2019. Mining’s contribution to national economies between 1996 and 2016. *Mineral Economics*, 32, 223–250. <https://doi.org/10.1007/s13563-019-00191-6> [Accessed 22 November 2020].
- Faul, F., Erdfelder, E., Buchner, A. & Lang, A., 2009. Statistical power analyses using G\*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods*, 41(4), 1149–1160.
- Faul, F., Erdfelder, E., Lang, A. & Buchner, A., 2007. G\*Power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, 39(2), 175–191.
- Fiedler, F.E., 1964. A contingency model of leadership effectiveness. *Advances in Experimental Social Psychology*, 1, 149–190. [Online] Available at: [https://doi.org/10.1016/s0065-2601\(08\)60051-9](https://doi.org/10.1016/s0065-2601(08)60051-9) [Accessed 2 November 2020].
- Furneaux, B., 2011. Task-technology fit theory: A survey and synopsis of the literature. *Information Systems Theory*, 1, 87–106. [Online] Available at: [https://doi.org/10.1007/978-1-4419-6108-2\\_5](https://doi.org/10.1007/978-1-4419-6108-2_5) [Accessed 23 November 2020].
- Gaur, A. & Gaur, S., 2009. *Statistical methods for practice and research: A guide to data analysis using SPSS*. 2nd ed. New Delhi: SAGE Publications.
- Ge, X. & Zhang, Y., 2011. From digital mine to smart mine. *Key Engineering Materials*, 480-481, 1607–1612.
- Ge, X., Su, S., Yu, H., Chen, G. & Lu, X., 2018. Smart mine construction based on knowledge engineering and internet of things. *International Journal of Performability Engineering*, 14(5), 1060–1068.

Gebauer, J. & Shaw, M.J., 2004. Success factors and impacts of mobile business applications: results from a mobile e-procurement study. *International Journal of Electronic Commerce*, 8(3), 19–41.

Gebauer, J. & Tang, Y., 2008. Applying the theory of task-technology fit to mobile technology: The role of user mobility. *International Journal of Mobile Communications*, 6, 321. [Online] Available at: <https://doi.org/10.1504/ijmc.2008.017514> [Accessed 23 November 2020].

Gebauer, J., Shaw, M.J. & Gribbins, M.L., 2010. Task-technology fit for mobile information systems. *Journal of Information Technology*, 25, 259–272. [Online] Available at: <https://doi.org/10.1057/jit.2010.10> [Accessed 4 November 2020].

Gefen, D., Straub, D. & Boudreau, M., 2000. Structural equation modeling and regression: Guidelines for research practice. *Communications of the Association for Information Systems*, 4(7). [Online] Available at: <http://dx.doi.org/10.17705/1CAIS.00407> [Accessed 14 November 2020].

Girod-Séville, M. & Perret, V., 2001. Epistemological foundations. Thiétart, R. (ed.), *Doing management research* (pp. 13–30). London: Sage Publications.

Global Mining Guidelines (GMG) Group, 2019, June 6. *Guideline for implementing short interval control in underground mining operations*. [Online] Available at: <https://gmgroup.org/publication-guideline-implementing-short-interval-control-underground-mining-operations/> [Accessed 2 November 2020].

Goodhue, D.L., 1995. Understanding user evaluations of information systems. *Management Science*, 41, 1827–1844. [Online] Available at: <https://doi.org/10.1287/mnsc.41.12.1827> [Accessed 23 November 2020].

Goodhue, D.L. & Thompson, R.L., 1995. Task-technology fit and individual performance. *MIS Quarterly*, 19(2), 213–236. [Online] Available at: <https://doi.org/10.2307/249689> [Accessed 24 November 2020].

Great Western Mining, 2020, March 9. *Great Western Mining: Investor presentation*. Great Western Mining Corporation plc. [Online] Available at: <http://www.proactiveinvestors.co.uk/LON:GWMO/Great-Western-Mining-Corporation-PLC/rns/791951> [Accessed 2 December 2020].

Hair, J.F., Hult, G.T.M., Ringle, C.M. & Sarstedt, M., 2017. *A primer on partial least squares structural equations modeling (PLS-SEM)*. 2nd ed. Los Angeles: SAGE.

- Hair, J., Ringle, C. & Sarstedt, M., 2011. PLS-SEM: Indeed a silver bullet. *Journal of Marketing Theory and Practice*, 19(2), 139-152.
- Harborth, D. & Pape, S., 2020. How privacy concerns, trust and risk beliefs, and privacy literacy influence users' intentions to use privacy-enhancing technologies. *ACM SIGMIS Database: The Database for Advances in Information Systems*, 51, 51–69. [Online] Available at: <https://doi.org/10.1145/3380799.3380805> [Accessed 3 November 2020].
- Hayes, A.F., 2013. *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. New York, NY: Guilford Press.
- Henderson, J.C. & Venkatraman, H., 1993. Strategic alignment: Leveraging information technology for transforming organizations. *IBM Systems Journal*, 32, 472–484. [Online] Available at: <https://doi.org/10.1147/sj.382.0472> [Accessed 2 November 2020].
- Henseler, J., Dijkstra, T.K., Sarstedt, M., Ringle, C.M., Diamantopoulos, A., Straub, D.W., Ketchen, D.J., Hair, J.F., Hult, G.T.M. & Calantone, R.J., 2014. Common beliefs and reality about PLS. *Organizational Research Methods*, 17(2), 182–209. [Online] Available at: <https://doi.org/10.1177/1094428114526928> [Accessed 24 November 2020].
- Hoening, J. & Heisey, D., 2001. The abuse of power: The pervasive fallacy of power calculations for data analysis. *The American Statistician*, 55(1), 19–24.
- Howard, M.C. & Rose, J.C., 2019. Refining and extending task-technology fit theory: Creation of two task-technology fit scales and empirical clarification of the construct. *Information & Management*, 56(6), 103134. [Online] Available at: <https://doi.org/10.1016/j.im.2018.12.002> [Accessed 22 November 2020].
- Howardson, G.N. & Behrend, T.S., 2016. Coming full circle with reactions: understanding the structure and correlates of trainee reactions through the affect circumplex. *Academic Management Learning Education*, 15(3), 471–492.
- Howes, R., Forrest, C., 2012. *Short interval control in today's underground mine: A case study*. Presented at MINExpo International 2012. [Online] Available at: [http://edstechnologies.com/Mailer/Sep15/Newsletter\\_September/images/ShortIntervalControl.pdf](http://edstechnologies.com/Mailer/Sep15/Newsletter_September/images/ShortIntervalControl.pdf) [Accessed 23 November 2020].
- Hu, L. & Bentler, P.M., 1999. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, 6, 1–55. [Online] Available at: <https://doi.org/10.1080/10705519909540118> [Accessed 2 November 2020].

- Huang, K. & Chuang, Y., 2016. A task–technology fit view of job search website impact on performance effects: An empirical analysis from Taiwan. *Cogent Business & Management*, 3(1), 1253943. [Online] Available at: <https://doi.org/10.1080/23311975.2016.1253943> [Accessed 22 November 2020].
- Ilie, V. & Turel, O., 2020. Manipulating user resistance to large-scale information systems through influence tactics. *Information & Management*, 57(3), 103178. [Online] Available at: <https://doi.org/10.1016/j.im.2019.103178> [Accessed 2 November 2020].
- Iyoubi, B. & Yamin, M., 2019. The impact of task technology fit on employee job performance. *Marketing and Management of Innovations*, 4, 140–159.
- Kademteme, E., Kalema, B. & Pretorius, P., 2015. *A structural equation model for data warehouse adoption in a government department*. 2015 IST-Africa Conference, 6-8 May, Lilongwe, Malawi.
- Kalika, M., 2020. *Anticipating the Managerial Impact of the DBA Thesis*. In: P. Beaulieu and M. Kalika, ed., *The DBA thesis project in practice*. Caen: Management et société, pp.139-150.
- Kalkandha, T., 2020. *7 Advantages of mobile apps for your business*. MobileAppAaily. [Online] Available at: <https://www.mobileappdaily.com/advantages-of-mobile-apps-for-business> [Accessed 2 January 2021].
- Kishokumar, R. & Thiyagarajan, P.T., 2015. *Influence of task-technology fit on individual job performance in insurance industry: Special reference to Batticaloa district*. 12th International Conference on Business Management (ICBM), 7–8 December, Sri Lanka, Colombo.
- Kock, N. & Hadaya, P., 2016. Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal*, 28(1), 227–261.
- Kock, N., 2015. Common method bias in PLS-SEM. *International Journal of e-Collaboration*, 11(4), 1–10.
- Kuhn, T., 1962. *The structure of scientific revolutions*. Chicago: University of Chicago Press.
- Lam, T., Cho, V. & Qu, H., 2007. A study of hotel employee behavioral intentions towards adoption of information technology. *International Journal of Hospitality Management*, 26(1), 49–65.
- Lean Manufacturing Posters, 2021. *PDCA poster*. [online] LEAN MANUFACTURING POSTERS. Available at: [https://www.leanmanufacturingposters.com/PDCA\\_p/pdca2228-1.htm](https://www.leanmanufacturingposters.com/PDCA_p/pdca2228-1.htm) [Accessed 31 August 2021].

Lee, C.-C., Cheng, H.K. & Cheng, H.-H., 2007. An empirical study of mobile commerce in insurance industry: Task-technology fit and individual differences. *Decision Support Systems*, 43, 95–110. [Online] Available at: <https://doi.org/10.1016/j.dss.2005.05.008> [Accessed 23 November 2020].

LePan, N., 2019. *Visualizing the potential of smart mining*. Visual Capitalist. [Online] Available at: <https://www.visualcapitalist.com/potential-smart-mining/> [Accessed 21 November 2020].

Lettig, S., 2020. *Information acquisition and knowledge conversion: Towards a routinized innovation process*. Unpublished EDDBA thesis. France: Business Science Institute / Université Jean Moulin Lyon 3.

Lin, T.-C., 2014. Mobile nursing information system utilization. *Computers, Informatics, Nursing (CIN)*, 32, 129–137. [Online] Available at: <https://doi.org/10.1097/cin.0000000000000039> [Accessed 22 November 2020].

Lohmöller, J.-B., 1989. *Latent variable path modeling with partial least squares*. Heidelberg: Physica-Verlag.

Lewis, J., 2019. *Vale Swings to Net Loss From Impact of Dam Disaster*. [online] WSJ. Available at: <https://www.wsj.com/articles/vale-swings-to-net-loss-from-impact-of-dam-disaster-11557443217> [Accessed 29 November 2020].

Maquinaria Magazine, 2012, December 21. *Sandvik automine system – Rio Tinto Northparkes Mine*. [Online] Available at: [https://www.youtube.com/watch?v=pwQi\\_DbMKmY](https://www.youtube.com/watch?v=pwQi_DbMKmY) [Accessed 2 January 2021].

Marikyan, D. & Papagiannidis, S., 2021. *Task technology fit*. Newcastle University. [Online] Available at: <https://open.ncl.ac.uk/theories/3/task-technology-fit/> [Accessed 2 December 2020].

Mayr, S., Erdfelder, E., Buchner, A. & Faul, F., 2007. A short tutorial of GPower. *Tutorials in Quantitative Methods for Psychology*, 3(2), 51–59.

McGill, T.J. & Hobbs, V.J., 2007. How students and instructors using a virtual learning environment perceive the fit between technology and task. *Journal of Computer Assisted Learning*, 24, 191–202. [Online] Available at: <https://doi.org/10.1111/j.1365-2729.2007.00253.x> [Accessed 3 December 2020].

McGill, T.J. & Klobas, J.E., 2009. A task-technology fit view of learning management system impact. *Computer Education*, 52(2), 496–508.

- McQuitty, S., 2004. Statistical power and structural equation models in business research. *Journal of Business Research*, 57(2), 175–183.
- Mikalef, P., Torvatn, H.Y. & Arica, E., 2019. Task-technology fit in manufacturing: Examining human-machine symbiosis through a configurational approach. *IFIP Advances in Information and Communication Technology*, 566, 624–632. [Online] Available at: [https://doi.org/10.1007/978-3-030-30000-5\\_76](https://doi.org/10.1007/978-3-030-30000-5_76) [Accessed 2 November 2020].
- Mining Association of Canada, 2019. *Mining facts*. Canada: The Mining Association of Canada.
- Mitchell, J., 2015. Barrick’s Turquoise Ridge Mine two-year safety and environmental achievements enhance mining’s reputation. *Nevada News and Views*, 7 September. [Online] Available at: <http://nevadanewsandviews.com/barrick-ridges-two-year-existence-cuts-off-the-bad-reputation-tied-in-to-mining-companies/> [Accessed 3 November 2020].
- Moore, G.C. & Benbasat, I., 1992. *An empirical examination of a model of the factors affecting utilization of information technology by end-users*. Working paper. Vancouver: University of British Columbia.
- Moore, G. & Benbasat, I., 1991. Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, 2(3), 192–222.
- Moore, P., 2019. *Barrick points to automation successes with Sandvik at Kibali & ASI Mining at South Arturo*. International Mining. [Online] Available at: <https://im-mining.com/2019/08/13/barrick-points-automation-successes-sandvik-kibali-asi-mining-south-arturo/> [Accessed 22 November 2020].
- Musyaffi, A.M. & Muna, A., 2020. *Task technology – Fit of a village financial system (Siskeudes) to increase officers' performance*. Knowledge E Publishing. [Online] Available at: <https://knepublishing.com/index.php/KnE-Social/article/view/6638> [Accessed 23 November 2020].
- Nance, W.D. & Straub, D.W. 1996. An investigation of task/technology fit and information technology choices in knowledge work. *Journal of Information Technology Management*, 7(3&4), 1–14.
- Nascimento, D., Alencastro, V., Quelhas, O., Caiado, R., Garza-Reyes, J., Rocha-Lona, L. & Tortorella, G., 2019. Exploring Industry 4.0 technologies to enable circular economy practices in a manufacturing context. *Journal of Manufacturing Technology Management*, 30(3), 607–627.

National Mining Association (NMA), 2019. *Minerals make life: Economic growth*. National Mining Association. [Online] Available at: <https://mineralsmakelife.org/economic-growth/> [Accessed 23 November 2020].

National Mining Association (NMA), 2018. *Barrick: Digitally transforming underground mining*. National Mining Association. [Online] Available at: <https://nma.org/2018/04/26/barrick-digitally-transforming-underground-mining/> [Accessed 25 November 2020].

Nevada Gold Mines, 2020. *Technical report on the Turquoise Ridge Complex, State of Nevada, USA*. Nevada: Nevada Gold Mines.

Nott, G., 2018. *Rio Tinto ramps up truck automation*. CIO. [Online] Available at: <https://www2.cio.com.au/article/631405/rio-tinto-ramps-up-truck-automation/> [Accessed 13 November 2020].

Pal, D. & Patra, S., 2020. University students' perception of video-based learning in times of COVID-19: A TAM/TTF perspective. *International Journal of Human-Computer Interaction*, 37(4), 1–19.

Pallud, J., 2017. Impact of interactive technologies on stimulating learning experiences in a museum. *Information & Management*, 54(4), 465–478.

Pearson, S. & Lewis, J., 2021. *Vale agrees to \$7 billion settlement for Brumadinho dam collapse*. WSJ. [Online] Available at: <https://www.wsj.com/articles/vale-agrees-to-7-billion-settlement-for-brumadinho-dam-collapse-11612446979> [Accessed 21 May 2021].

PricewaterhouseCoopers (PwC), 2016. *Industry 4.0: Building the digital enterprise*, 6. PwC. [Online] Available at: <https://www.pwc.com/gx/en/industries/industries-4.0/landing-page/industry-4.0-building-your-digital-enterprise-april-2016.pdf> [Accessed 2 February 2021].

Rahm, S., 2013. *Mining the ESG ground*. Research paper. London: Schroders. [Online] Available at: [https://www.schroders.com/en/sysglobalassets/staticfiles/Schroders/Sites/global/pdf/Mining\\_the\\_ESG\\_Ground\\_report\\_December\\_2013.pdf](https://www.schroders.com/en/sysglobalassets/staticfiles/Schroders/Sites/global/pdf/Mining_the_ESG_Ground_report_December_2013.pdf) [Accessed 2 January 2021].

Rai, R. & Selnes, F., 2019. Conceptualizing task-technology fit and the effect on adoption – A case study of a digital textbook service. *Information & Management*, 56(8), 103161. [Online] Available at: <https://doi.org/10.1016/j.im.2019.04.004> [Accessed 24 January 2021].

Ringle, C.M., Wende, S. & Becker, J.-M., 2015. *Smart PLS 3*. Bönningstedt: SmartPLS.

- Ritchie, J. & Lewis, J., 2014. *Qualitative research practice: A guide for social science students and researchers*. London: Sage.
- Robles-Flores, J.A. & Roussinov, D., 2012. *Examining question-answering technology from the task technology fit perspective*. *Communications of the Association for Information Systems*, 30. [Online] Available at: <https://doi.org/10.17705/1cais.03026> [Accessed 13 November 2020].
- Saunders, M., Lewis, P. & Thornhill, A., 2009. *Research methods for business students*. 5th ed. Harlow: Pearson Education Limited.
- Savit, Z., Kunam, K. & Sawant, A., 2018. *Short interval control with groundHog*. Rapidbizapps. [Online] Available at: <https://rapidbizapps.com/wp-content/uploads/2018/03/Short-Interval-Control-in-Mining-1.pdf> [Accessed 12 November 2020].
- Sawyer, A. & Ball, A., 1981. Statistical power and effect size in marketing research. *Journal of Marketing Research*, 18(3), p.275-290.
- Schmelzer, R., 2020. AI and the digital mine. *Forbes*, 28 May. [Online] Available at: <https://www.forbes.com/sites/cognitiveworld/2020/05/28/ai-and-the-digital-mine/#70b175f4703e> [Accessed 6 June 2020].
- Sekaran, U. & Bougie, R., 2013. *Research methods for business*. 6th ed. New York: Wiley.
- Shehzad, A. & Rozan, M.Z.A., 2018. Potential fit between geotechnical tasks and mobile computing technologies. *International Journal of Engineering & Technology*, 7(3.7), 4. [Online] Available at: <https://doi.org/10.14419/ijet.v7i3.7.16194> [Accessed 13 November 2020].
- SmartPLS, 2021. *Model fit*. SmartPLS. [Online] Available at: <https://www.smartpls.com/documentation/algorithms-and-techniques/model-fit> [Accessed 2 March 2021].
- Spies, R., Grobbelaar, S. & Botha, A., 2020. A scoping review of the application of the task-technology fit theory. In: Hattingh, M., Matthee, M., Smuts, H., Pappas, I., Dwivedi, Y.K. & Mäntymäki, M. (Eds.), *Responsible design, implementation and use of information and communication technology* (pp. 397–408). Cham.: Springer International Publishing.
- Staples, D.S. & Seddon, P., 2004. Testing the technology-to-performance chain model. *Journal of Organizational and End User Computing*, 16(4), 17–36. [Online] Available at: <https://doi.org/10.4018/joeuc.2004100102> [Accessed 3 November 2020].

- Statista, 2020. *Topic: Smartphones*. [Online] Available at: [www.statista.com](http://www.statista.com) [Accessed 2 November 2020].
- Strong, D.M., Dishaw, M.T. & Bandy, D.B., 2006. Extending task technology fit with computer self-efficacy. *ACM SIGMIS Database*, 37(2-3), 96–107.
- Swanson, L.R. & Bellanca, J.L., 2018. *Task exploring fit to improve mine safety: A NIOSH project on mobile proximity detection systems*. New Mexico: Bureau of Mine Safety.
- Tam, C. & Oliveira, T., 2019. Does culture influence m-banking use and individual performance? *Information & Management*, 56(3), 356–363.
- Venkatesh, V., Morris, M.G., Davis, G.B. & Davis, F.D. 2003. User acceptance of information technology: Toward a unified view. *MIS Quarterly*, 27(3), 425–478. [Online] Available at: <https://doi.org/10.2307/30036540> [Accessed 2 November 2020].
- Vessey, I., 1991. Cognitive fit: A theory-based analysis of the graphs versus tables literature. *Decision Sciences*, 22, 219–240. [Online] Available at: <https://doi.org/10.1111/j.1540-5915.1991.tb00344.x> [Accessed 2 November 2020].
- Visser, W., 2020. A blueprint for performance-driven operations management. *Mining, Metallurgy & Exploration*, 37(3), 823–831.
- Von Hippel, E., 1986. Lead users: A source of novel product concepts. *Management Science*, 32, 791–805. [Online] Available at: <https://doi.org/10.1287/mnsc.32.7.791> [Accessed 3 November 2020].
- Wold, H.O.A., 1982. Soft modeling: The basic design and some extensions. In K.G. Jöreskog & H. Wold (eds.), *Systems under indirect observation: causality, structure, prediction* (Volume 2, pp. 1–54). Amsterdam: North Holland.
- Wold, H.O.A., 1975. Soft modelling by latent variables: The Non-Linear Iterative Partial Least Squares (NIPALS) Approach. *Journal of Applied Probability*, 12(S1), 117-142.
- World Economic Forum (WEF), 2020. *Mining and metals: Digital transformation and the industry's "new normal"*. Switzerland: World Economic Forum. [Online] Available at: <https://reports.weforum.org/digital-transformation/mining-and-metals-digital-transformation-and-the-industrys-new-normal/> [Accessed 23 November 2020].
- World Economic Forum (WEF), 2017. *Digital transformation initiative mining and metals industry – In collaboration with Accenture*. Switzerland: World Economic Forum. [Online] Available at: <https://reports.weforum.org/digital-transformation/wp-content/blogs.dir/94/mp/files/pages/files/wef-dti-mining-and-metals-white-paper.pdf> [Accessed 15 November 2020].

- Wu, I.-L., Li, J.-Y. & Fu, C.-Y., 2011. The adoption of mobile healthcare by hospital's professionals: An integrative perspective. *Decision Support Systems*, 51, 587–596. [Online] Available at: <https://doi.org/10.1016/j.dss.2011.03.003> [Accessed 2 November 2020].
- Xu, Y., Wei, J., Zhou, X. & Sun, F., 2019. Application and development of Smart Mine in China. *MATEC Web of Conferences*, 295, p.02005.
- Yu, T.-K. & Yu, T.-Y., 2010. Modelling the factors that affect individuals' utilisation of online learning systems: An empirical study combining the task technology fit model with the theory of planned behaviour. *British Journal of Educational Technology*, 41(6), 1003–1017. [Online] Available at: <https://doi.org/10.1111/j.1467-8535.2010.01054.x> [Accessed 3 November 2020].
- Zhao, M., 2020. Technology of internet of things technology in the construction of Smart Mine. *2020 3rd International Conference on Artificial Intelligence and Big Data (ICAIBD)*, pp. 289–292. doi: 10.1109/ICAIBD49809.2020.9137475 [Accessed 2 November 2020].
- Zhou, T., Lu, Y. & Wang, B., 2010. Integrating TTF and UTAUT to explain mobile banking user adoption. *Computers in Human Behavior*, 26, 760–767. [Online] Available at: <https://doi.org/10.1016/j.chb.2010.01.013> [Accessed 3 November 2020].
- Zhou, V., 2019. *BHP to roll out autonomous trucks at QLD coal mine*. Australian Mining. [Online] Available at: <https://www.australianmining.com.au/news/bhp-to-roll-out-autonomous-trucks-at-qld-coal-mine/> [Accessed 3 March 2021].
- Zigurs, I. & Buckland, B.K., 1998. A theory of task/technology fit and group support systems effectiveness. *MIS Quarterly*, 22(3), 313–334. [Online] Available at: <https://doi.org/10.2307/249668> [Accessed 2 February 2021].

## APPENDICES

### Appendix A – Indirect testing results

Hypothesis	Original Sample (O)	Sample Mean (M)	Bias	2.50%	97.50%
SIC Task Characteristics -> Task Technology Fit (TTF) -> Underground Miner Reactions	0.108	0.124	0.016	-0.033	0.28
Mobile Technology Characteristics -> Task Technology Misfit (TTM) – "Too Little" -> Utilization	-0.036	-0.042	-0.006	-0.131	0.047
Mobile Technology Characteristics -> Task Technology Misfit (TTM) – "Too Little" -> Utilization -> Performance Output	-0.018	-0.023	-0.005	-0.096	0.021
SIC Task Characteristics -> Task Technology Misfit (TTM) – "Too Much" -> Underground Miner Reactions	0.001	-0.001	-0.001	-0.03	0.032
SIC Task Mobile TTM Much -> Task Technology Misfit (TTM) – "Too Much" -> Underground Miner Reactions	-0.005	-0.007	-0.003	-0.062	0.006
SIC Task Characteristics -> Task Technology Misfit (TTM) – "Too Much" -> Utilization -> Performance Output	-0.001	0.001	0.002	-0.022	0.025
SIC Task Mobile TTM Small -> Task Technology Misfit (TTM) – "Too Little" -> Underground Miner Reactions	0.009	0.009	0	-0.021	0.057
SIC Task Characteristics -> Task Technology Misfit (TTM) – "Too Little" -> Underground Miner Reactions	0.006	0.006	-0.001	-0.014	0.074
SIC Task Characteristics -> Task Technology Misfit (TTM) – "Too Little" -> Performance Output	-0.015	-0.009	0.006	-0.147	0.015
SIC Task Characteristics -> Task Technology Misfit (TTM) – "Too Little" -> Utilization	-0.008	-0.012	-0.004	-0.071	0.01
SIC Task Mobile TTM Small -> Task Technology Misfit (TTM) – "Too Little" -> Utilization	-0.01	-0.013	-0.002	-0.055	0.011
SIC Task Characteristics -> Task Technology Fit (TTF) -> Utilization -> Performance Output	0.057	0.072	0.015	-0.01	0.217

<b>Hypothesis</b>	<b>Original Sample (O)</b>	<b>Sample Mean (M)</b>	<b>Bias</b>	<b>2.50%</b>	<b>97.50%</b>
SIC Task Mobile TTF -> Task Technology Fit (TTF) -> Utilization	0.051	0.055	0.004	-0.041	0.166
Mobile Technology Characteristics -> Task Technology Fit (TTF) -> Performance Output	0.308	0.277	-0.031	0.125	0.636
SIC Task Mobile TTM - "Too Little" -> Task Technology Misfit (TTM) - "Too Little" -> Performance Output	-0.021	-0.013	0.007	-0.112	0.023
SIC Task Characteristics -> Task Technology Misfit (TTM) - "Too Much" -> Performance Output	0	-0.001	-0.001	-0.053	0.051
SIC Task Mobile TTF -> Task Technology Fit (TTF) -> Utilization -> Performance Output	0.026	0.034	0.008	-0.015	0.14
Mobile Technology Characteristics -> Task Technology Misfit (TTM) - "Too Much" -> Utilization -> Performance Output	0.034	0.041	0.007	0	0.139
Mobile Technology Characteristics -> Task Technology Fit (TTF) -> Utilization -> Performance Output	0.225	0.247	0.022	0.057	0.588
Mobile Technology Characteristics -> Task Technology Misfit (TTM) - "Too Much" -> Underground Miner Reactions	-0.036	-0.041	-0.005	-0.193	0.049
SIC Task Mobile TTM Small -> Task Technology Misfit (TTM) - "Too Little" -> Utilization -> Performance Output	-0.005	-0.007	-0.002	-0.038	0.005
SIC Task Characteristics -> Task Technology Fit (TTF) -> Utilization	0.113	0.127	0.014	-0.03	0.295
SIC Task Mobile TTM Much -> Task Technology Misfit (TTM) - "Too Much" -> Utilization	0.009	0.011	0.003	-0.008	0.056
Task Technology Misfit (TTM) - "Too Much" -> Utilization -> Performance Output	-0.072	-0.083	-0.011	-0.249	0.003
SIC Task Characteristics -> Task Technology Misfit (TTM) - "Too Little" -> Utilization -> Performance Output	-0.004	-0.006	-0.003	-0.045	0.005
Mobile Technology Characteristics -> Task Technology Fit (TTF) -> Utilization	0.447	0.445	-0.002	0.205	0.668
SIC Task Mobile TTF -> Task Technology Fit (TTF) -> Underground Miner Reactions	0.049	0.053	0.004	-0.041	0.154

<b>Hypothesis</b>	<b>Original Sample (O)</b>	<b>Sample Mean (M)</b>	<b>Bias</b>	<b>2.50%</b>	<b>97.50%</b>
Mobile Technology Characteristics -> Task Technology Misfit (TTM) – "Too Little" -> Performance Output	-0.07	-0.034	0.036	-0.258	0.093
SIC Task Mobile TTM Much -> Task Technology Misfit (TTM) – "Too Much" -> Utilization -> Performance Output	0.004	0.006	0.002	-0.003	0.039
Mobile Technology Characteristics -> Task Technology Fit (TTF) -> Underground Miner Reactions	0.426	0.432	0.006	0.19	0.631
Task Technology Misfit (TTM) – "Too Little" -> Utilization -> Performance Output	0.039	0.05	0.011	-0.043	0.185
SIC Task Mobile TTM Much -> Task Technology Misfit (TTM) – "Too Much" -> Performance Output	0.001	-0.002	-0.004	-0.031	0.053
SIC Task Characteristics -> Task Technology Fit (TTF) -> Performance Output	0.078	0.076	-0.002	-0.001	0.237
Task Technology Fit (TTF) -> Utilization -> Performance Output	0.375	0.402	0.027	0.116	0.815
Mobile Technology Characteristics -> Task Technology Misfit (TTM) – "Too Much" -> Utilization	0.068	0.077	0.01	-0.002	0.21
SIC Task Mobile TTF -> Task Technology Fit (TTF) -> Performance Output	0.035	0.031	-0.004	-0.013	0.131
Mobile Technology Characteristics -> Task Technology Misfit (TTM) – "Too Little" -> Underground Miner Reactions	0.03	0.031	0.001	-0.076	0.148
SIC Task Characteristics -> Task Technology Misfit (TTM) – "Too Much" -> Utilization	-0.001	0.001	0.002	-0.042	0.044
Mobile Technology Characteristics -> Task Technology Misfit (TTM) – "Too Much" -> Performance Output	0.01	-0.013	-0.023	-0.208	0.209

**Appendix B – Cross loadings for discriminant validity**

<b>Construct/ Observable variable</b>	<b>Underground Miner Reactions</b>	<b>Performance Output</b>	<b>SIC Task Characteristics</b>	<b>Mobile Technology Characteristics</b>	<b>Task Technology Fit (TTF)</b>	<b>Task Technology Misfit (TTM) – "Too Little"</b>	<b>Task Technology Misfit (TTM) – "Too Much"</b>	<b>Utilization</b>
Miner React 1	<b>0.816</b>	0.463	0.346	0.399	0.575	-0.462	-0.388	0.588
Miner React 2	<b>0.955</b>	0.533	0.591	0.746	0.674	-0.401	-0.405	0.731
Miner React 3	<b>0.947</b>	0.543	0.6	0.773	0.66	-0.431	-0.396	0.726
Perfor Impacts 1	0.494	<b>0.921</b>	0.594	0.491	0.616	-0.352	-0.412	0.56
Perfor Impacts 2	0.541	<b>0.959</b>	0.59	0.504	0.655	-0.38	-0.413	0.595
Perfor Impacts 3	0.51	<b>0.939</b>	0.545	0.491	0.572	-0.366	-0.374	0.545
Perfor Impacts 4	0.547	<b>0.93</b>	0.578	0.557	0.63	-0.377	-0.456	0.582
Perfor Impacts 5	0.573	<b>0.972</b>	0.607	0.519	0.636	-0.405	-0.451	0.606
Perfor Impacts 6	0.547	<b>0.964</b>	0.564	0.535	0.621	-0.404	-0.437	0.592
Perfor Impacts 7	0.55	<b>0.963</b>	0.583	0.525	0.624	-0.406	-0.453	0.595
SIC Task 1	0.518	0.546	<b>0.889</b>	0.532	0.377	-0.219	-0.219	0.433
SIC Task 2	0.526	0.57	<b>0.893</b>	0.553	0.354	-0.199	-0.199	0.415
SIC Task 3	0.488	0.595	<b>0.919</b>	0.479	0.416	-0.214	-0.155	0.419
SIC Task 4	0.471	0.517	<b>0.861</b>	0.479	0.392	-0.238	-0.173	0.348
SIC Task 5	0.459	0.435	<b>0.868</b>	0.43	0.296	-0.176	-0.116	0.293
SIC Task 6	0.52	0.509	<b>0.791</b>	0.395	0.36	-0.173	-0.177	0.358
SIC Tech 1	0.535	0.436	0.406	<b>0.756</b>	0.499	-0.407	-0.363	0.59
SIC Tech 2	0.509	0.283	0.321	<b>0.802</b>	0.472	-0.325	-0.328	0.515
SIC Tech 3	0.709	0.364	0.44	<b>0.886</b>	0.567	-0.458	-0.39	0.622
SIC Tech 4	0.623	0.427	0.42	<b>0.864</b>	0.498	-0.293	-0.267	0.586
SIC Tech 5	0.545	0.432	0.441	<b>0.828</b>	0.509	-0.268	-0.302	0.576
SIC Tech 6	0.663	0.379	0.44	<b>0.873</b>	0.604	-0.36	-0.384	0.728
SIC Tech 7	0.501	0.332	0.308	<b>0.744</b>	0.555	-0.389	-0.469	0.635

Construct/ Observable variable	Underground Miner Reactions	Performance Output	SIC Task Characteristics	Mobile Technology Characteristics	Task Technology Fit (TTF)	Task Technology Misfit (TTM) – "Too Little"	Task Technology Misfit (TTM) – "Too Much"	Utilization
SIC Tech 8	0.528	0.328	0.303	<b>0.823</b>	0.418	-0.303	-0.263	0.483
SIC Tech 9	0.525	0.647	0.687	<b>0.644</b>	0.48	-0.345	-0.291	0.477
SIC Tech 10	0.501	0.716	0.617	<b>0.707</b>	0.507	-0.343	-0.362	0.512
TTF 1	0.713	0.648	0.421	0.639	<b>0.933</b>	-0.614	-0.64	0.782
TTF 2	0.653	0.615	0.43	0.65	<b>0.945</b>	-0.64	-0.651	0.747
TTF 3	0.653	0.574	0.402	0.549	<b>0.914</b>	-0.541	-0.53	0.702
TTF 4	0.572	0.554	0.312	0.547	<b>0.879</b>	-0.58	-0.637	0.642
TTF 5	0.603	0.641	0.361	0.601	<b>0.901</b>	-0.619	-0.591	0.744
TTF 6	0.647	0.551	0.386	0.566	<b>0.906</b>	-0.564	-0.543	0.691
TTM Small 1	-0.433	-0.338	-0.192	-0.399	-0.62	<b>0.85</b>	0.598	-0.438
TTM Small 2	-0.385	-0.345	-0.223	-0.362	-0.569	<b>0.841</b>	0.631	-0.376
TTM Small 3	-0.346	-0.311	-0.145	-0.308	-0.514	<b>0.842</b>	0.657	-0.41
TTM Small 4	-0.451	-0.429	-0.245	-0.41	-0.531	<b>0.893</b>	0.616	-0.502
TTM Small 5	-0.404	-0.34	-0.184	-0.414	-0.566	<b>0.884</b>	0.621	-0.464
TTM Small 6	-0.438	-0.342	-0.232	-0.425	-0.6	<b>0.915</b>	0.626	-0.458
TTM Much 1	-0.414	-0.423	-0.179	-0.359	-0.571	0.615	<b>0.922</b>	-0.527
TTM Much 2	-0.42	-0.423	-0.221	-0.425	-0.588	0.614	<b>0.891</b>	-0.574
TTM Much 3	-0.301	-0.326	-0.124	-0.316	-0.566	0.571	<b>0.79</b>	-0.399
TTM Much 4	-0.427	-0.521	-0.232	-0.407	-0.641	0.655	<b>0.919</b>	-0.553
TTM Much 5	-0.374	-0.34	-0.209	-0.413	-0.513	0.651	<b>0.888</b>	-0.484
TTM Much 6	-0.369	-0.343	-0.088	-0.408	-0.616	0.706	<b>0.913</b>	-0.509
Utilization 1	0.734	0.57	0.454	0.703	0.704	-0.427	-0.512	<b>0.913</b>
Utilization 2	0.686	0.695	0.399	0.664	0.771	-0.522	-0.559	<b>0.923</b>
Utilization 3	0.629	0.357	0.331	0.618	0.663	-0.428	-0.495	<b>0.891</b>

**Appendix C – Fornell-Larcker criterion**

<b>Construct</b>	<b>Mobile Technology Characteristics</b>	<b>Performance Output</b>	<b>SIC Task Characteristics</b>	<b>Task Technology Fit (TTF)</b>	<b>Task Technology Misfit (TTM) – "Too Much"</b>	<b>Task Technology Misfit (TTM) – "Too Little"</b>	<b>Underground Miner Reactions</b>	<b>Utilization</b>
Mobile Technology Characteristics	0.796							
Performance Output	0.545	0.95						
SIC Task Characteristics	0.552	0.611	0.871					
Task Technology Fit (TTF)	0.65	0.656	0.424	0.913				
Task Technology Misfit (TTM) – "Too Much"	-0.439	-0.451	-0.201	-0.656	0.888			
Task Technology Misfit (TTM) – "Too Little"	-0.446	-0.405	-0.235	-0.65	0.715	0.871		
Underground Miner Reactions	0.715	0.566	0.571	0.703	-0.436	-0.472	0.908	
Utilization	0.729	0.613	0.438	0.789	-0.576	-0.509	0.753	0.909

**Appendix D – Confidence intervals bias corrected table**

<b>Path Coefficient</b>	<b>Original Sample (O)</b>	<b>Sample Mean (M)</b>	<b>Bias</b>	<b>2.50%</b>	<b>97.50%</b>
Mobile Technology Characteristics -> Task Technology Fit (TTF)	0.635	0.628	-0.007	0.383	0.809
Mobile Technology Characteristics -> Task Technology Misfit (TTM) – "Too Much"	-0.507	-0.513	-0.005	-0.678	-0.308
Mobile Technology Characteristics -> Task Technology Misfit (TTM) – "Too Little"	-0.468	-0.47	-0.002	-0.647	-0.267
SIC Task Mobile TTF -> Task Technology Fit (TTF)	0.061	0.065	0.003	-0.065	0.179
SIC Task Characteristics -> Task Technology Fit (TTF)	0.098	0.121	0.023	-0.116	0.314
SIC Task Characteristics -> Task Technology Misfit (TTM) – "Too Much"	0.029	0.014	-0.015	-0.186	0.261
SIC Task Characteristics -> Task Technology Misfit (TTM) – "Too Little"	-0.087	-0.105	-0.017	-0.345	0.133
SIC Task Mobile TTM Much -> Task Technology Misfit (TTM) – "Too Much"	-0.032	-0.041	-0.01	-0.142	0.114
SIC Task Mobile TTM Small -> Task Technology Misfit (TTM) – "Too Little"	-0.123	-0.134	-0.01	-0.242	0.022
TTF Utilization Perform -> Performance Output	0.183	0.18	-0.002	-0.21	0.605
TTM Much Utilization Perform -> Performance Output	0.096	0.055	-0.04	-0.503	0.616
TTM Small Utilization Perform -> Performance Output	-0.113	-0.023	0.09	-0.57	0.405
Task Technology Fit (TTF) -> Performance Output	0.482	0.431	-0.05	0.09	0.956
Task Technology Fit (TTF) -> Underground Miner Reactions	0.523	0.535	0.012	0.221	0.74
Task Technology Fit (TTF) -> Utilization	0.729	0.728	-0.001	0.506	0.915
Task Technology Misfit (TTM) – "Too Much" -> Performance Output	-0.144	-0.104	0.04	-0.588	0.255
Task Technology Misfit (TTM) – "Too Much" -> Underground Miner Reactions	0.114	0.121	0.006	-0.135	0.43
Task Technology Misfit (TTM) – "Too Much" -> Utilization	-0.159	-0.177	-0.018	-0.423	-0.008
Task Technology Misfit (TTM) – "Too Little" -> Performance Output	0.207	0.14	-0.067	-0.109	0.52
Task Technology Misfit (TTM) – "Too Little" -> Underground Miner Reactions	-0.207	-0.205	0.001	-0.552	0.11
Task Technology Misfit (TTM) – "Too Little" -> Utilization	0.071	0.089	0.017	-0.112	0.27
Utilization -> Performance Output	0.457	0.503	0.046	0.045	0.944

## Appendix E – Latent variable loadings

Construct	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
1.Miner_React_1	1	0.395	0.456	0.287	0.289	0.291	0.288	0.339	0.38	0.284	0.207	0.283	0.38	0.349	0.257	0.593	0.564	0.451	0.487	0.541	0.387	0.378	0.366	0.456	0.399	0.416	0.369	0.234	0.373	0.302	0.538	0.578	0.476
2.Perform_Impacts_1	0.395	1	0.826	0.533	0.522	0.521	0.442	0.504	0.343	0.619	0.31	0.362	0.369	0.288	0.572	0.595	0.543	0.534	0.577	0.52	0.323	0.273	0.246	0.372	0.289	0.318	0.407	0.311	0.451	0.323	0.511	0.638	0.333
3.Perform_Impacts_2	0.456	0.826	1	0.533	0.561	0.467	0.405	0.502	0.423	0.702	0.279	0.417	0.365	0.311	0.629	0.625	0.545	0.506	0.627	0.531	0.326	0.368	0.317	0.427	0.319	0.358	0.422	0.299	0.534	-0.34	0.544	0.691	0.334
4.SIC_Task_1	0.287	0.533	0.533	1	0.797	0.658	0.713	0.682	0.426	0.55	0.315	0.388	0.42	0.24	0.684	0.368	0.345	0.289	0.346	0.316	0.158	0.207	0.143	0.258	0.156	-0.21	-0.25	0.142	0.243	0.226	0.461	0.394	0.313
5.SIC_Task_2	0.289	0.522	0.561	0.797	1	0.733	0.775	0.599	0.375	0.566	0.341	0.475	0.453	0.322	0.645	0.392	0.318	0.234	0.302	0.294	0.144	0.172	0.124	0.244	0.139	0.201	0.222	-0.129	0.214	0.203	0.423	0.381	0.32
6.SIC_Task_4	0.291	0.521	0.467	0.658	0.733	1	0.705	0.528	0.343	0.515	0.306	0.393	0.369	0.36	0.52	0.349	0.382	0.298	0.314	0.415	-0.22	0.191	0.157	0.207	0.198	0.265	0.146	0.138	0.183	0.185	0.368	0.322	0.248
7.SIC_Task_5	0.28	0.442	0.405	0.713	0.775	0.705	1	0.682	0.301	0.485	0.258	0.337	0.353	0.215	0.524	0.296	0.302	0.24	0.218	0.259	0.166	0.175	-0.08	0.201	0.134	0.149	0.089	0.087	0.131	0.155	0.318	0.241	0.24
8.SIC_Task_6	0.339	0.504	0.502	0.682	0.599	0.528	0.682	1	0.243	0.522	0.206	0.30	0.33	0.162	0.602	0.371	0.329	0.273	0.306	0.328	0.144	0.216	-0.13	0.156	0.096	0.167	0.238	0.041	0.227	0.186	0.358	0.32	0.295
9.SIC_Tech_1	0.38	0.343	0.423	0.426	0.375	0.343	0.301	0.243	1	0.527	0.484	0.573	0.649	0.577	0.462	0.488	0.442	0.398	0.519	0.373	-0.33	0.349	0.284	0.387	0.445	-0.32	0.373	0.254	0.373	0.303	0.603	0.554	0.433
10.SIC_Tech_2	0.284	0.619	0.702	0.55	0.566	0.515	0.485	0.522	0.527	1	0.461	0.622	0.463	0.395	0.635	0.52	0.424	0.418	0.49	0.404	-0.27	0.343	0.268	-0.3	0.318	0.297	0.326	0.233	0.402	-0.34	0.498	0.526	0.347
11.SIC_Tech_3	0.207	0.31	0.279	0.315	0.341	0.306	0.258	0.206	0.484	0.461	1	0.651	0.667	0.621	0.293	0.423	0.392	0.4	0.468	0.415	0.294	0.277	0.204	0.253	0.264	0.396	0.304	0.233	0.302	0.444	0.515	0.437	
12.SIC_Tech_4	0.283	0.362	0.417	0.388	0.475	0.393	0.337	0.305	0.573	0.622	0.651	1	0.7	0.605	0.502	0.511	0.436	0.423	0.445	0.464	0.264	0.229	0.218	-0.17	0.228	0.295	0.327	-0.16	0.294	0.256	0.536	0.54	0.49
13.SIC_Tech_5	0.38	0.369	0.365	0.424	0.453	0.369	0.353	0.336	0.649	0.463	0.667	0.7	1	0.68	0.523	0.614	0.516	0.486	0.55	0.541	0.329	-0.27	0.263	0.342	0.344	0.319	0.372	0.233	0.347	0.388	0.682	0.621	0.7
14.SIC_Tech_6	0.349	0.288	0.311	0.24	0.322	0.36	0.215	0.162	0.577	0.395	0.621	0.605	0.68	1	0.314	0.501	0.527	0.519	0.456	0.498	0.343	0.247	-0.35	0.323	0.364	0.403	0.381	-0.4	0.388	0.463	0.614	0.558	0.563
15.SIC_Tech_7	0.257	0.572	0.629	0.684	0.645	0.524	0.602	0.462	0.462	0.635	0.293	0.502	0.523	0.314	1	0.492	0.359	0.43	0.449	0.413	-0.29	0.331	0.227	0.368	0.284	-0.29	0.301	0.238	0.305	0.285	0.487	0.408	0.406
16.TTF_1	0.593	0.595	0.625	0.368	0.392	0.349	0.296	0.371	0.488	0.52	0.423	0.511	0.614	0.501	0.492	1	0.827	0.763	0.815	0.807	0.587	0.534	0.494	0.527	-0.54	0.531	0.616	0.516	0.635	0.481	0.679	0.767	0.678
17.TTF_2	0.564	0.543	0.545	0.345	0.318	0.382	0.302	0.329	0.442	0.424	0.392	0.436	0.516	0.527	0.359	0.827	1	0.763	0.761	0.852	0.517	0.475	0.395	0.444	0.482	0.511	-0.45	0.483	0.521	-0.41	0.65	0.68	0.57
18.TTF_3	0.451	0.534	0.506	0.289	0.234	0.298	0.244	0.273	0.398	0.418	0.4	0.423	0.486	0.519	0.43	0.763	0.763	1	0.74	0.776	0.598	0.512	0.469	0.458	0.489	0.513	0.542	0.588	0.607	0.524	0.589	0.618	0.534
19.TTF_4	0.487	0.577	0.627	0.346	0.302	0.314	0.218	0.306	0.519	0.49	0.468	0.445	0.55	0.456	0.449	0.815	0.761	0.74	1	0.738	0.534	0.588	0.485	0.525	0.551	0.554	0.524	0.483	0.606	0.471	0.643	0.752	0.617
20.TTF_5	0.541	0.52	0.531	0.316	0.294	0.415	0.259	0.328	0.373	0.404	0.415	0.464	0.541	0.498	0.413	0.807	0.852	0.776	0.738	1	0.566	0.441	0.404	0.448	0.499	0.579	0.472	0.482	0.513	0.401	0.614	0.664	0.601
21.TTM_Small_1	0.387	0.323	0.326	0.158	0.144	-0.22	0.166	-0.144	-0.33	-0.27	0.294	0.264	0.333	0.343	0.29	0.587	0.517	0.598	0.534	0.566	1	0.638	0.66	0.658	0.694	0.788	0.496	0.537	0.53	0.386	0.455	0.338	
22.TTM_Small_2	0.378	0.273	0.368	0.207	0.172	0.191	0.175	-0.216	0.349	0.343	0.277	0.229	0.27	0.247	0.33	0.534	0.475	0.512	0.588	0.441	0.638	1	0.723	0.675	0.676	0.721	0.551	0.473	0.665	0.538	-0.31	0.376	0.334
23.TTM_Small_3	0.366	0.246	0.317	0.143	0.124	0.157	0.08	-0.13	0.284	0.268	0.204	0.218	0.26	-0.35	0.23	0.494	0.395	0.469	0.485	0.404	0.66	0.723	1	0.671	0.654	0.747	0.572	0.453	0.675	0.541	0.317	0.419	0.378
24.TTM_Small_4	0.456	0.372	0.427	0.258	0.244	0.207	0.201	-0.156	0.387	-0.3	0.253	-0.17	0.34	0.323	0.37	0.527	0.444	0.458	0.525	0.448	0.658	0.675	0.671	1	0.838	0.784	0.507	0.517	0.515	0.641	0.434	0.505	0.421
25.TTM_Small_5	0.399	0.289	0.319	0.156	0.139	0.198	0.134	-0.096	0.445	0.318	0.264	0.228	0.34	0.364	0.28	-0.54	0.482	0.489	0.551	0.499	0.694	0.676	0.654	0.838	1	0.733	0.543	0.527	0.518	0.577	-0.38	-0.46	0.425

Construct	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33
26.TTM_Small 6	0.416	0.318	0.358	-0.21	0.201	0.265	0.149	-0.167	-0.32	0.297	0.396	0.295	-	0.403	0.29	0.531	0.511	0.513	0.554	0.579	0.788	0.721	0.747	0.784	0.733	1	0.554	0.489	0.55	0.567	0.388	-0.5	0.336
27.TTM_Small 7	0.369	0.407	0.422	-0.25	0.222	0.146	0.089	-0.238	0.373	0.326	0.304	0.327	-	0.381	-0.3	0.616	0.483	0.542	0.524	0.472	0.496	0.551	0.572	0.507	0.543	0.554	1	0.623	0.792	0.689	0.478	-0.58	-0.5
28.TTM_Small 8	0.234	0.311	0.299	0.142	0.129	0.138	0.087	-0.041	0.254	0.233	0.233	-0.16	0.23	-0.4	0.24	0.516	0.483	0.588	0.483	0.482	0.52	0.473	0.453	0.517	0.527	0.489	0.623	1	0.643	0.671	-0.37	0.357	0.364
29.TTM_Small 9	0.373	0.451	0.534	0.243	0.214	0.183	0.131	-0.227	0.373	0.402	0.302	0.294	0.35	0.388	0.31	0.635	0.521	0.607	0.606	0.513	0.537	0.665	0.675	0.515	0.518	0.55	0.792	0.643	1	0.763	-0.49	0.559	0.444
30.TTM_Much 4	0.302	0.323	-0.34	0.226	0.203	0.185	0.155	-0.186	0.303	-0.34	0.301	0.256	0.39	0.463	0.29	0.481	0.679	0.524	0.471	0.401	0.531	0.538	0.541	0.641	0.577	0.567	0.689	0.671	0.763	1	0.485	0.418	0.418
31.Utilization 1	0.536	0.511	0.544	0.461	0.423	0.368	0.318	0.358	0.603	0.498	0.444	0.536	0.682	0.614	0.487	0.679	0.65	0.589	0.643	0.614	0.386	-0.31	0.317	0.434	-0.38	0.388	0.478	-0.37	-0.49	0.485	1	0.747	0.744
32.Utilization 2	0.578	0.638	0.691	0.394	0.381	0.322	0.241	0.32	0.554	0.526	0.515	0.54	0.621	0.558	0.408	0.767	0.68	0.618	0.752	0.664	0.455	0.376	0.419	0.505	-0.46	-0.5	-0.58	0.357	0.559	0.418	0.747	1	0.736
33.Utilization 3	0.476	0.333	0.334	0.313	0.32	0.248	0.24	0.295	0.433	0.347	0.437	0.49	0.7	0.563	0.406	0.678	0.57	0.534	0.617	0.601	0.338	0.334	0.378	0.421	0.425	0.336	-0.5	0.364	0.444	0.418	0.744	0.736	1

## Appendix F - Questionnaire

### 1. SECTION 1: DEMOGRAPHIC INFORMATION

The length to fill this questionnaire is approximately 15 minutes. Kindly select where applicable

\* 1. Gender

- Male
- Female
- Opt-out

\* 2. Employment category

- Hourly
- Salary
- Opt-out

\* 3. Age Group

- 20-29
- 30-39
- >39
- Opt - out

\* 4. Position level in organization

- Top Management (e.g., Managers, GM etc.)
- Middle Management(e.g., General Supervisors, Superintendents etc.)
- Technical Services(e.g., Mine Engineers, Geologists, Surveyors, Geotech etc.)
- Front Line Supervisors (e.g., Supervisors, Leadman)
- General (Underground Miner, Operator, Maintenance etc.)
- Opt-out

\* 5. Work experience in the mining industry

- Less than a year
- 1 to 5 years
- 6 to 10 years
- More than 10 years
- Opt-out

**\* 6. Primary business functional area**

- Underground Mining Operations
- Engineering
- Health, Safety and Environment
- Administration i.e. HR, IT, Supply Chain etc.
- Opt-out

**\* 7. Highest education attained**

- High School Diploma
- Associate Degree
- Bachelor's degree
- Graduate degree
- Opt-out

## 2. SECTION 2: STATEMENTS ABOUT UNDERGROUND EMPLOYEE CHARACTERISTICS AND SYSTEM ADOPTION

In this section, several statements are provided regarding how you are comfortable with using or operating SIC mobile technology systems. Using your experience, select the appropriate option in each case.

8. Rank how frequent you use the SIC mobile technology systems to do your job

	Never	Very Rarely	Rarely	Occasionally	Frequently	Very Frequently	Opt out
Cisco Webex teams(Spark) for communicating	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Deswik Ops for scheduling	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
groundHog for reporting and resource management	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Mobilaris for resource management and situational awareness	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Outlook Email for communication	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Power BI for viewing report trends	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
iPads for accessing mobile apps	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
iPhone for access mobile apps	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

\* 9. How many months have you been using SIC mobile technology systems?

- < 6 months
- 6 - 12 months
- 12-24 months
- >24 months
- Opt-out

10. Rank your level of competence in using the SIC mobile technology systems to perform your underground short interval control tasks e.g as planning, communication, resource management, operational decision making, etc

	Extremely Poor	Below Average	Average	Above Average	Excellent	Opt out
Cisco Webex teams(Spark)	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Deswik Ops	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
groundHog	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Mobilaris	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Outlook Email	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Power BI	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
iPads	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
iPhone	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

### 3. SECTION 3: STATEMENTS ABOUT USER REACTIONS TO SIC MOBILE TECHNOLOGIES

In this section, there are several statements regarding the user reactions to using underground short interval control mobile technology systems. Using your experience, select the appropriate option in each case.

11. What are your reactions to using Mobile-enabled SIC technologies to do your job?

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree	Opt out
I am passionate and enthusiastic about SIC Mobile technologies	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I am generally positive about SIC Mobile technologies	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I do not see SIC Mobile technologies as a distraction to my work	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I get support from IT to use SIC Mobile technologies	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

#### 4. SECTION 4: STATEMENTS ABOUT UNDERGROUND SHORT INTERVAL CONTROL TASK CHARACTERISTICS

**Global Mining Guidelines classify underground short interval control tasks as (1) Planning, e.g., life of mine planning, medium-term, and weekly/shift schedules, (2) Situation awareness, e.g., control center tracking team members and asset locations, (3) Resource management, e.g., equipment, asset, and qualified personnel availability reporting, and (4) Operational decision making, e.g., knowledge and action based on schedules, tactical or operational plans.**

**In this section, they are several statements regarding the characteristics of underground short interval control tasks . Using your experience, select the appropriate option in each case.**

\* 12. My job requires performing the **same type of tasks**

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree

\* 13. My job **depends** on using SIC Mobile Technology systems

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree

\* 14. My job requires the performance of a wide **variety of tasks**

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree

\* 15. I often have to **coordinate my activities** with others

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree

\* 16. The way I work has a **big impact on others**

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree

\* 17. My own performance depends on **obtaining correct information** from others

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree

\* 18. My job involves participating in **Underground meetings** e.g Shift Planning, line out meetings, weekly meetings, etc

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree

\* 19. My job involves **passing correct information** to others

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree

\* 20. My own performance depends on **acting** on correct information from others

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree

\* 21. My own performance depends on checking the **correctness of information** in SIC mobile technology systems

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree

\* 22. My own performance depends on **adjusting** what I need to do based on new information communicated using SIC mobile technology systems

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree

## 5. SECTION 5: STATEMENTS ABOUT SHORT INTERVAL CONTROL MOBILE TECHNOLOGY SYSTEMS CHARACTERISTICS

**Underground Short Interval Control mobile technology systems include Mobile hardware, e.g., iPad/iPhone devices and mobile applications, e.g., groundhog & Deswik Ops, Mobilaris, Power BI, Outlook email, and Cisco Webex teams (Spark). In this section, several statements regarding the characteristics of underground short interval control mobile technology systems are provided. Using your experience, select the appropriate option in each case.**

\* 23. I can use the SIC mobile technology device and applications I need, regardless of where I am i.e Surface, Underground

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

\* 24. If I use SIC mobile technology systems, I can easily communicate with co-workers

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

\* 25. I can collaborate with my co-workers through the use of SIC mobile technology systems

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

\* 26. Mobile-enabled SIC technologies have features that stimulate me to use them to perform my SIC tasks

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

\* 27. SIC mobile technology systems provides real-time services

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

28. Mobile-enabled SIC technologies have the following features that stimulate me to use them to perform my SIC tasks

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree	Opt out
Portability	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Screen Size	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Weight	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Digital Camera	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Useful Mobile Apps in Single location e.g. Cisco Webex teams, groundHog etc.	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Connectivity	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Touch Screen	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
Single Windows	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

## 6. SECTION 6: STATEMENTS ABOUT SHORT INTERVAL CONTROL TASK FIT AND MISFIT

In this section, several statements regarding the features of underground short interval control mobile technology systems are provided. Using your experience, select the appropriate option in each case.

29. An iPad and mobile apps allow for **accessing information quickly and easily**

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree	Opt out
My iPad and apps <b>lack these features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have <b>too much features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have features that <b>suits</b> performing this task	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

30. An iPad and mobile apps allows for accessing **accurate information** for work purposes

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree	Opt out
My iPad and apps <b>lack these features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have <b>too much features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have features that <b>suits</b> performing this task	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

31. An iPad and mobile apps are **easy to learn and use**

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree	Opt out
My iPad and apps <b>lack these features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have <b>too much features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have features that <b>suits</b> performing this task	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

32. An iPad and mobile apps provide **consistent information that can be consolidated**

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree	Opt out
My iPad and apps <b>lack these features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have <b>too much features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have features that <b>suits</b> performing this task	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

33. An iPad and mobile apps provide **up - to - date information** which I need to do my work

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree	Opt out
My iPad and apps <b>lack these features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have <b>too much features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have features that <b>suits</b> performing this task	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

34. An iPad and mobile apps **do not confuse** when needed in a given situation

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree	Opt out
My iPad and apps <b>lack these features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have <b>too much features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have features that <b>suits</b> performing this task	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

35. An iPad and mobile apps are **convenient and easy to use**

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree	Opt out
My iPad and apps <b>lack these features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have <b>too much features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have features that <b>suits performing this task</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

36. An iPad and mobile apps allow for **easy location of information**

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree	Opt out
My iPad and apps <b>lack these features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have <b>too much features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have features that <b>suits</b> performing this task	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

37. An iPad and mobile apps allow for **understanding the exact meaning of information** as it relates to the task at hand

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree	Opt out
My iPad and apps <b>lack these features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have <b>too much features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have features that <b>suits</b> performing this task	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

38. An iPad and mobile apps **present information in a readable and useful format.**

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree	Opt out
My iPad and apps <b>lack these features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have <b>too much features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have features that <b>suits</b> performing this task	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

39. An iPad and mobile apps provide the appropriate **level of detail of information**

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree	Opt out
My iPad and apps <b>lack this feature</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have <b>too much features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have features that <b>suits</b> performing this task	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

40. An iPad and mobile apps are always **online and available**. They do not experience frequent problems and crashes

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree	Opt out
My iPad and apps <b>lack these features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have <b>too much features</b>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
My iPad and apps have features that <b>suits</b> performing this task	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

## 7. SECTION 7: STATEMENTS ABOUT EFFORT EXPECTANCY ON SHORT INTERVAL CONTROL MOBILE TECHNOLOGY SYSTEMS

**In this section, there are several statements regarding the effort expectancy of short interval control mobile systems. Using your experience, you are requested to select the appropriate option in each case.**

\* 41. Using the SIC mobile technology systems skillfully is easy for me

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

\* 42. I find using SIC mobile technology systems easy.

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

\* 43. My interaction with SIC mobile technology systems is clear and understandable.

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

## 8. SECTION 8: STATEMENTS ABOUT FACILITATING CONDITIONS WHEN USING MOBILE SIC SYSTEMS

**In this section, there are several statements regarding the facilitating conditions of short interval control mobile systems. Using your experience, you are requested to select the appropriate option in each case.**

\* 44. I have the necessary resources to use SIC mobile technology systems

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

\* 45. I have the necessary knowledge to use SIC mobile technology systems

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

\* 46. If I have difficulty using SIC mobile technology systems, there are professionals to help me.

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

## 9. SECTION 9: STATEMENTS ABOUT SOCIAL INFLUENCE ON MOBILE SHORT INTERVAL CONTROL SYSTEMS

**In this section, there are several statements regarding the social influence of short interval control mobile technology systems. Using your experience, you are requested to select the appropriate option in each case.**

\* 47. Those people that influence my behavior at work think that I should use mobile technology systems e.g iPad, Cisco Webex, groundhog

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

\* 48. Those people that are important to me at work think that I should use SIC mobile technology systems e.g iPad, Cisco Webex, groundhog

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

## 10. SECTION 10: STATEMENTS ABOUT UTILIZATION OF SIC MOBILE TECHNOLOGY

In this section, they are several statements regarding the utilization of underground short interval control mobile technology systems. Using your experience, select the appropriate option in each case.

49. What are your reactions to using Mobile-enabled SIC technologies to do your job?

	Strongly disagree	Disagree	Slightly disagree	Neither agree nor disagree	Slightly agree	Agree	Strongly agree	Opt out
I have become very dependent on the Mobile-enabled SIC technologies to do my job	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
I believe that I use the Mobile-enabled SIC technologies as intended by my organization	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>
SIC Mobile technologies and I are two entities that get along well with each other	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

## 11. SECTION 11: STATEMENTS ABOUT PERFORMANCE IMPACTS OF SHORT INTERVAL CONTROL MOBILE SYSTEMS

**In this section, there are several statements regarding the performance impacts of short interval control mobile systems . Using your experience, you are requested to select the appropriate option in each case.**

\* 50. Using the SIC mobile technology systems e.g iPad, Cisco Webex, groundhog has a **positive impact** on my work

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

\* 51. My **quality of my work** has improved through the use of SIC mobile technology systems e.g iPad, Cisco Webex, groundhog

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

\* 52. I make **better operational decisions** by using SIC mobile technology systems e.g iPad, Cisco Webex, groundhog

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

\* 53. I can do my job **faster** by using SIC mobile technology systems e.g iPad, Cisco Webex, groundhog

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

\* 54. SIC mobile technology systems e.g iPad, Cisco Webex, groundhog helps achieve my **production and safety targets**

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

\* 55. I am **efficient** at my work because I use SIC mobile technology systems e.g iPad, Cisco Webex, groundhog e.t.c

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

\* 56. SIC mobile technology systems e.g iPad, Cisco Webex, groundhog e.t.c improves my **convenience** to do my job

- Strongly agree
- Agree
- Slightly agree
- Neither agree nor disagree
- Slightly disagree
- Disagree
- Strongly disagree
- Opt Out

## DETAILED OVERVIEW OF THESIS

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