

**AN ASSESSMENT OF BUSINESS INTELLIGENCE TOOLS' FITNESS IN
SUPPORTING DECISIONS MAKING PROCESSES IN SOUTH AFRICA'S
UNIVERSITIES OF TECHNOLOGY: A CASE OF THE CUT**

by

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DEDICATION

To the Almighty God, My Saviour, the source of endless wisdom and strength, through whom all things are possible. To my pillars of strength, my dear parents, Mnkabane and Mamtshawe who may not be with me today, but whose words of wisdom echo in my heart and guide my steps every day: **“NEVER GIVE UP.”**

To my mother-in-law, Hlabs whose unwavering faith and cheer have constantly reminded me to push through and persevere against all odds. To my anchor, my loving husband, Dlamini, whose patience, understanding and boundless support have been my rock. And to my dearest sons, Mzo and Sima for their sacrifices, love and for being the driving force behind every page of this research. Your endless patience, love and encouragement have made this journey possible.

This work stands as a testament to the collective love, faith and resilience of all those who've walked this path with me.

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PUBLICATIONS

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DECLARATION

I declare that “An Assessment of Business Intelligence Tools’ Fitness In Supporting Decision-making Processes In South Africa’s Universities Of Technology: Case of CUT” is my original work, and I correctly referenced every source I have used or taken information from.

I further affirm that I have never before submitted this work, in whole or in part, for examination at CUT for another qualification or at any other higher education institution.

Vuyiswa Njokweni (_____)

SEPTEMBER 2023

Full name and student number

Signature _____

Date:

In my role as the supervisor of this dissertation, I certify that the aforementioned claims are accurate to the best of my knowledge.

Signature _____

Date

ABSTRACT

The pervasive integration of Business Intelligence (BI) systems within academic institutions underscores their pivotal role in fostering data-driven decision-making. Nevertheless, grasping the intricate web of factors influencing BI fitness for decision-making in academia remains daunting. This dissertation contributes towards bridging this knowledge gap by harnessing Structural Equation Modelling (SEM) to unravel the multifaceted elements underpinning BI systems effectiveness in facilitating decision-making processes, especially by middle-level managers. An extensive case study was conducted at the Central University of Technology, Free State (CUT) where the institution depends on the Integrated Tertiary Software (ITS) as its BI system. The research methodology was thoughtfully crafted to guarantee the attainment of strong and scientifically sound outcomes. A quantitative research approach was used to collect data. This entailed the distribution of an online survey questionnaire through the SurveyMonkey. The survey achieved a 70% response rate, with 42 out of the targeted 60 academic teaching and support staff participating. These respondents predominantly held middle management positions and utilised ITS to inform their decision-making roles. The collected dataset underwent a thorough analysis, commencing with descriptive data analysis conducted using IBM Statistical Software for Social Sciences version 27.

Additional data analysis in the form of SEM, using SmartPLS 4 was used to undertake an extensive analysis of the measurement model (outer model) and the structural model (inner model). Through SEM, a comprehensive evaluation of the fundamental components of this study is conducted. These components encompass (1) the current positions of the respondents, (2) their utilisation of systems, (3) the attributes defining the tasks they engage in, (4) the compatibility of these tasks with the technology in use (or Task-Technology-Fitness, otherwise known as TTF) and (5) the inherent characteristics of the technology itself. In addition, an assessment of the reliability and discriminant validity of these constructs was performed in order to establish a strong and dependable basis upon which a subsequent analysis was built. This emphasises the crucial role played by the assurance of both the consistency and distinctiveness of these foundational elements in ensuring the overall strength and validity of the research findings.

The structural model findings shed light on the factors influencing the appropriateness of BI for decision-making. TTF emerges as a pivotal factor, demonstrating a strong and positive impact on the effectiveness of BI in supporting decision-making in academic contexts. Conversely, system usage has a comparatively weaker influence in this context. The dissertation extends to explore effect size () and path coefficients, providing a glimpse into the strength and significance of these interrelationships. Specific hypotheses are scrutinised, with results either confirming or challenging initial hypotheses. The research validates the significant influence of current position on system usage while negating the substantial impact of task characteristics and system usage on TTF.

To summarise concisely, after conducting extensive tests on the Inner Model, which included assessments like R-Square, F-Square, and Q-Square, we found that while the standardized Root Mean Square Residual (SRMR = 0.120) exceeds the acceptable threshold of 0.08, and the Normed Fit Index (NFI = 0.430) falls short of the desired benchmark of 0.90, when considering all these results together, they suggest a positive fit between the model and the data. The key finding is therefore the critical significant impact of TTF and technology characteristics on the effectiveness of BI for decision-making tasks.

This dissertation offers a substantial contribution to comprehending BI fitness within academic contexts. The findings accentuate the pivotal role of TTF and its far-reaching implications for fortifying BI systems in academia. These insights can potentially steer strategic decisions, optimise resource allocation, and cultivate data-driven academic ecosystems. The research highlights the necessity of using strong methodologies and SEM techniques to uncover the complex dynamics that govern BI in the academic sphere.

Keywords:

Business intelligence, Decision making, Integrated Tertiary Software, Partial least square structural equation model, Task Technology Fit,

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LIST OF ABBREVIATIONS

•	APP	Annual Performance Plan
•	BI	Business Intelligence
•	CASE	Computer-Aided Software Engineering
•	CB-SEMI	Covariance-Based Structural Equation Modeling
•	CUT	Central University of Technology, Free State
•	CRM	Customer Relationship Management
•	DMP	Decision-Making Process
•	DSS	Decision Support System
•	DHET	Department of Higher Education and Training
•	DW	Data Warehousing
•	EIS	Executive Information Systems
•	ES	Enterprise Systems
•	ERP	Enterprise Resource Planning
•	ETL	Extract, Transform, Load
•	IPQE	Institutional Planning and Quality Enhancement
•	IS	Information Systems
•	ITS	Integrated Tertiary Software
•	IDSS	Intelligent Decision Support Systems
•	MIS	Management Information System
•	NFI	Normed Fit Index
•	OLTP	Online Transaction Processing
•	PLS-SEM	Partial Least Squares Structured Equation Modeling
•	SPSS	Statistical Package for the Social Sciences
•	SRMR	Standardized Root Mean Square Residual
•	TAM	Technology Acceptance Model
•	TIM	Technology Infusion Model
•	TTF	Task Technology Fit
•	UoT	University of Technology
•	UTAUT	Unified Theory of Acceptance and Use of Technology

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CHAPTER 1: INTRODUCTION

1.1 Overview

A fundamental facilitator for digital strategies, Business Intelligence (BI) provides a suite of methods and tools specifically designed to ensure effortless access and efficient management of information. This entails orchestration of data collection, storage, distribution, and ultimate exploitation, as expounded by Safary (2020). In response to burgeoning demands for technological sophistication in the business realm, characterised by an exponential surge in data volume across diverse business systems, BI has assumed an integral role, finding extensive adoption within organisations, particularly those fervently pursuing digital transformation. The systematic application of BI processes empowers organisations to ascend the echelons of scalability, intelligence, and adaptability in their decision-making processes, as posited by Ramasamy (2020).

The storm of technological transformations, sweeping across all sectors, including the global academia landscape, has accelerated the need for digital strategies and mechanisms to augment data-driven decision-making. In this context, universities around the globe have enthusiastically adopted digital strategies, utilising valuable insights to strengthen the decision-making process, as highlighted in the groundbreaking research conducted by Hamad et al. (2022). Within this realm, BI has emerged as an indispensable digital tool, composed of a myriad of interconnected systems, poised to enhance decision-making, economise costs, streamline processes, and elevate the calibre of pedagogical offerings, as expounded upon by Abduldaem & Gravell (2021). The relevance of BI tools in the academic sphere rests upon their capacity to provide stakeholders with an all-encompassing vista of the institution, undergirded by strategic insights. These insights are the anchor for swifter, more precise, and more dependable decision-making processes, encapsulating the quintessence of BI's transformative potential (Abduldaem & Gravell, 2021).

The decision-making process (DMP) involves a dynamic interplay between data and knowledge originating from a numerous of sources and forms draw close within the organisational framework 2019). Knowledge workers and managers utilise BI to support their decision-making process (Abdelrahman, 2019). In harmoniousness with the evolution of big-data ecosystems, DMP has been seamlessly integrated into contemporary organisational paradigms to expand the decision-making organisation (Parra et al., 2022).

The cautious merging of BI and analytics is indicated as a basis of innovation and agility across numerous industry verticals. BI expands the efficiency of DMP by grouping, warehousing, and scrutinising data, metamorphosing it into insights that serve as the crucible within which managers forge decisions designed to revitalise organisational performance (Lahbi, 2018).

Considering the scarcity of studies evaluating the effectiveness of BI tools in supporting organisational DMP, this study aimed at assessing the fitness of a specific BI tool in the context of decision-making tasks. The analytical framework of this inquiry focused on three critical dimensions: (1) the inherent characteristics of the technology, (2) the nature of tasks executed in support of decision-making processes, and (3) the degree of congruence between task technology and the current responsibilities assigned to academic and support managers. Adopting a case study methodology, this investigation centred on examining the Integrated Tertiary Online Software (ITS online), which is the BI system deployed at the Central University of Technology, Free State (CUT).

1.2 Problem Statement

Decision-making, underpinned by BI systems, stands as a cornerstone of innovation and agility within the academic landscape of universities, as articulated by Tavera Romero *et al.* (2021). Highlighting the crucial significance of data-informed decision-making in this context, South Africa's Department of Higher Education and Training (DHET) issued Government Notice 464 (DHET, 2014), which introduced the Regulations for Reporting by Public Higher Education Institutions. This regulatory framework applies universally to all public higher education institutions, mandating the formulation of a comprehensive five-year Strategic Plan and Annual Performance Plan (APP). The APP crafting takes cues from the DHET Annual Performance Plan, encompassing facets of planning and budgeting, necessitating seamless alignment with the overarching strategic plan (DHET, 2014). From this perspective, the relationship between the university's strategic plan and BI systems becomes critically important, serving as an essential cornerstone for successfully carrying out the strategic objectives (Niño *et al.*, 2020).

Pertaining to this crucial issue, the CUT, is effectively implementing its strategic plan, Annual Performance Plan (APP), along with its complex internal reporting structures. Obtaining accurate data from the current BI system, the Integrated Tertiary Software Online System (ITS), used for decision-making by academic and support managers, presents a significant hurdle. This issue underscores the urgent necessity for a thorough assessment of ITS fitness for decision-making tasks. This study aims to address this gap by

applying the Task-Technology-Fit (TTF) model, as articulated by Goodhue & Thompson (1995), to assess the degree to which ITS aligns with the decision-making tasks of middle-level managers.

1.3 Aim of the Study

Aligned with the stated problem, this study aims to assess the fitness of Integrated Tertiary Software (ITS) in facilitating decision-making processes at the CUT. Utilising the Task-Technology-Fit (TTF) model, to assess the degree of alignment between ITS and the decision-making responsibilities carried out by managers. We assess the capabilities of ITS in improving decision making process within the context of CUT.

In activity of this leading objective, the study examines the effectiveness of BI tools in enhancing decision-making efforts at CUT. The ultimate goal is to assess BI's suitability for various tasks, optimize the benefits of data-driven decision-making, and make a meaningful contribution to the university's advancement and competitive position. This is accomplished by addressing the research questions presented below:

- **RQ1:** What are the technological characteristics of BI tools commonly used by South African Universities of Technology (UoTs)?
- **RQ2:** What are the primary tasks executed by academic and support managers Universities of Technology (UoTs) in South Africa, and which of these tasks can be effectively supported and enhanced through the utilisation of BI for decision-making processes?
- **RQ3:** How should an Information System model be structured to appraise the fitness of BI technology for decision-making processes within South African UoTs?

These research questions outline our path towards fulfilling the main goal of the study and meet into the following research objectives:

- **RO1:** To comprehensively examine the technological attributes characterising BI tools commonly employed in South African UoTs.
- **RO2:** To differentiate and describe the principal tasks executed by managers at the University of Technology (UoTs) in South Africa, undergo a thorough task-technology-fitness assessment to determine their appropriateness for facilitating high-quality decision-making. emphasising tasks entailing student-related processes. Subsequently, the identified tasks undergo a thorough task-technology-fitness assessment to determine their appropriateness for facilitating high-quality decision-making.

- **RO3:** To leverage the Task-Technology-Fit Model in the design and evaluation of ITS' aptitude for fostering quality decision-making at the CUT.

1.4 Scope and Limitation of the Study

The emphasis of this research is specifically on assessing the fitness of the online Integrated Tertiary Software (ITS) as the designated BI system utilized by academic and support managers at the CUT in Bloemfontein, Free State province. Participation in the SurveyMonkey questionnaire conducted online refer to Annexure 4: Research Instrument-SurveyMonkey Online Questionnaire was restricted to academic and support managers actively engaged in decision-making processes dependent on ITS within their current professional roles at the Bloemfontein campus. The task-technology model constructed for this study primarily seeks to interpret the relationship among the current job, task characteristics, technology characteristics, and Task-Technology Fit characteristics. It is essential to recognize that the reliance on a singular case study involving middle managers in this study may constrain the generalizability of the resulting framework in its current form. Mitigation measures for the limitation of relying on a singular case study involving middle managers include conducting research with a broader sample size to enhance the generalizability of the resulting framework and considering comparative case studies or cross-institutional analyses to validate the findings.

1.5 Ethical Considerations

Ethical clearance for this study was granted by the Faculty of Engineering, Built Environment, and Information Technology Research and Innovation Committee of the Central University of Technology, Free State (CUT). The ethical clearance certificate is included as Annexure 3: Research Ethical Clearance. Ethical Clearance with a reference number FEBIT 4/19-610/25-04-2019). The research adhered to all ethical procedures and protocols stipulated by CUT. The investigation, which included gathering data from managers at the Central University of Technology, Free State (CUT) using the online Integrated Tertiary Software (ITS), followed a strict code of ethics. Participation in the research was entirely voluntary, and a commitment to maintaining the principles of confidentiality and anonymity was upheld. All participants provided informed consent. Additionally, a letter was drafted to encourage the targeted employees to

participate in the online SurveyMonkey questionnaire. This communication, along with the survey link, was distributed via email.

1.6 Importance and contribution of the study

The outcomes of this research significantly advance our comprehension of BI in its capacity to execute decision-related tasks. It provides a comprehensive understanding of the technological attributes and task characteristics that promote the execution of decision-related tasks, specifically within a South African university of technology context. Despite the widespread adoption of BI tools in universities globally for data analysis, examining tasks and technology characteristics' impact on decision-making processes, particularly within the CUT has been notably absent. This study aimed to bridge this knowledge gap, shedding light on the intricate aspects of BI tools within this context. The study's significance spans both the academic and practical domains, contributing to several key areas.

Firstly, this research addresses a noticeable gap in the academic literature by extensively assessing the factors that affect the fitness of BI for decision-making within academic institutions. It uncovers the complex dynamics at play in this particular setting. Secondly, as universities increasingly rely on data-driven decision-making for resource optimisation, improved student outcomes, and overall institutional performance, this study's findings offer invaluable insights into the effective utilisation of BI systems to support decision-making processes in universities.

On the other hand, the insights gleaned from this study can inform strategic resource allocation within academic institutions. By understanding which factors wield significant influence over BI fitness, institutions can allocate resources more judiciously, enhancing the performance of their BI systems. In addition, academic institutions can utilise the study's insights to cultivate environments where data analytics and BI tools are seamlessly integrated into decision-making processes. This fosters a culture of evidence-based decision-making, propelling institutions into the data-driven era.

Additionally, this study's thorough utilisation of Structural Equation Modeling (SEM) stands as a methodological example, emphasising the significance of employing advanced statistical techniques for analysing complex relationships within academic contexts. The practical implications extend beyond academia to academic administrators, policymakers, and educators. They can harness the findings to enhance the effectiveness of their BI systems, ultimately leading to improved institutional performance.

The study lays a solid foundation for future research effort in BI fitness for decision-making within academic institutions. The findings can build up to explore additional factors, contexts, and methodologies. In an era marked by heightened competitiveness among academic institutions, the ability to make data-informed decisions confers a substantial advantage. The study's insights empower institutions to strengthen their competitiveness through the more effective utilisation of BI systems.

1.7 Outline of the Dissertation

This dissertation is structured into five chapters, each carefully organized and outlined:

Chapter 1: Establishes the foundation by presenting the study context, outlining the research objectives and questions, and providing a rationale for the research. Additionally, this chapter discusses the limitations of the study.

Chapter 2: Explores an extensive literature review, offering brief summaries of relevant studies that form the basis for assessing the fitness of BI tools.

Chapter 3: Explains the research methodology framework, justifying the adoption of a quantitative research approach and discussing the broader research design in detail.

Chapter 4: Takes on the responsibility of data analysis and the discussion of results.

Chapter 5: Adopts a reflective perspective, engaging in a discourse on the findings, presenting avenues for additional research, and concluding with the study's final remarks.

CHAPTER 2: LITERATURE REVIEW

2.1 Overview

A detailed analysis of the literature on business intelligence (BI) and theories linked to system usage are presented in this chapter. The clarification on the process that was employed in this assessment is done at the outset of the review. Subsequently, it investigates into various aspects of BI, including its existing setting of expertise mechanisms evolution, and its role in decision-making. The chapter covers topics such as BI's overview, definitions, functions, and benefits. It also explores the Decision-Making Process (DMP) and Decision Support Systems (DSS) as integral components of BI (Abdelrahman, 2019). The more, It Integrated Tertiary Software (ITS) as the BI system utilised at the Central University of Technology, Free State (CUT). The literature review culminates in the presentation of the theoretical framework that will guide the study in addressing the research question.

BI tools have gained significant attention in higher education, particularly in universities. BI technology has emerged as a digital tool in different sectors. Many systems feed it and can be used at different operational, tactical, and strategic decision levels. These tools offer advanced analytics and data-driven insights to support decision-making processes and enhance organisational performance (Damar, 2022).

Today's data-driven environment has led to an increase in the value of BI in decision-making among enterprises across industries. Organisations can convert large amounts of data into useful information using BI tools and methodologies, enabling them to spot trends, patterns, and linkages that can inform strategic and operational choices. BI is the term used to describe the technology, tools, and methodologies that enable organisations to gather, analyse, and present data meaningfully to support decision-making (Boulila et al., 2018). This literature review aims to provide an overview of the existing research and studies related to assessing BI tools' fitness in supporting decision-making processes in South Africa's universities of technology, specifically focusing on the case of the CUT.

2.2 Evolution of Business Intelligence

BI can be traced back to the 1950s when businesses started using computers to automate manual processes. However, the term BI was coined in the 1980s and used in multiple businesses in the 1990s and early 2000s, involving integrating data from multiple sources into a single system. The term was initially popularised by H. P. Luhn (1958), who described it as business and intelligent systems. BI has the ability for the view and analysis of the data for sights into a data set. Business analytics intelligence integrates BI and the analytics process for the frontier of the research development of productivity (Sun, 2020).

BI has been around for a long time and has seen several iterations. Early versions focused on data analysis to help managers make decisions (Tripahti *et al.*, 2020). At the same time, more recent incarnations encompass dashboards and predictive modelling that enable businesses to gain deeper insights into their customers better improve predictions about future trends (Niu *et al.*, 2021). BI systems are used by financial institutions, healthcare, retail, manufacturing, and hospitality. The systems are used to track performance metrics, optimise pricing statistics, improve customer satisfaction, and optimise supply chain management (Brill, 2019). BI has evolved significantly, reflecting technological changes and the growing emphasis on decision-making based on data in organisations (Mutaz *et al.*, 2021). BI has its roots in the early days of computing but has evolved significantly over the years (Tavera *et al.*, 2021). Today, BI continues to evolve as modern technologies emerge and companies seek new ways to gain insights from data (Tripahti *et al.* 2021).

2.3 BI Definitions

BI solutions enable firms to make data-driven decisions that improve their performance and competitiveness by extracting useful information from huge and complicated data sets using advanced analytics techniques (Grigorescu *et al.*, 2020). While Toic *al.*, (2022) define BI as a set of methodologies, tools, and technologies that help gather critical information from various unstructured data sources and transform it into knowledge that can be applied to improve business decision-making.

BI enables businesses to use massive amounts of data and combine them into a competitive advantage-generating decision support system (Scholtz *et al.*, 2018), Jooste (2022) view BI as gathering, storing, analysing and disseminating information which allow organisations to make better decisions.

BI encompasses many activities, including data warehousing, decision support software, and Big Data processing. Many BI tools and applications can help businesses achieve their goals. Some common functions include reporting, analysis, performance management, and BI mapping. Performance management enables you to identify areas where improvements can be made so that the organisation achieves its objectives more efficiently, according to Rikhardsson & Yigitbasioglu (2018). BI is a set of tools and techniques to analyse and interpret data. It can be broadly divided into multiple categories: operational intelligence, marketing intelligence, financial intelligence, supply chain management, human capital management, performance analytics, and product development. However, Rikhardsson & Yigitbasioglu (2018) agree that BI helps organisations to use data and technology in real-time and provide intelligent insights to make them more productive and analytical.

BI platforms allow users to understand their business better to make informed decisions. It can improve operational efficiency by providing real-time visibility into key performance indicators (KPIs), understanding customer dynamics, forecasting trends, and identifying potential risks. BI also improves communication between various parts of an organisation by facilitating the exchange of information across channels such as emails, phone lines, and workstations (Torres *et al.*, 2018).

2.4 Business Intelligence (BI) Architecture

The BI architecture is a framework that enables data consolidation, segmentation, or restructuring to process a wide range of inquiries pertinent to the user's area of interest. The BI architecture is depicted in the form five layers, which are the (1) data source layer, (2) Extract-Transform-Load (ETL) layer, (3) integration layer, (4) processing layer, and (5) visualization layer (Villegas-Ch *et al.*, 2020).

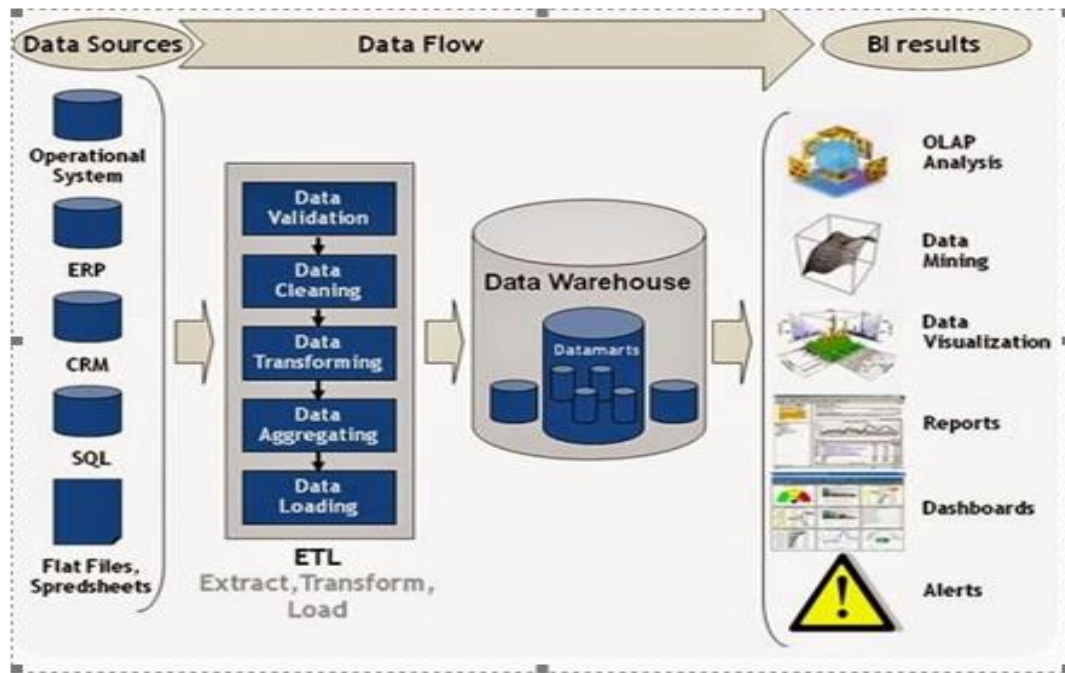


Figure 1: BI Architecture (Boulila et al. 2018)

2.4.1 Data Sources Layer

Data sources include internal or external operational databases that contain files in structured formats like comma-separated values (csv) and extensible mark-up language (xml) that combine structured, semi-structured, and unstructured data (Mora et al., 2023). The data source may also come from significant sources like social media (Bustamante et al., 2020).

2.4.2 Extract-Transform-Load Layer (ETL)

ETL is a procedure used to extract data from non-OLTP systems such as spreadsheets, legacy systems, text files, and online transaction processing (OLTP) databases. The data is then transformed to conform to the data warehouse schema before being put into the database. Finally, the data is turned into high-quality information utilising OLAP analysis, data mining, data visualisations, or other BI approaches to satisfy all business reporting requirements for all levels of users (Boulila et al., 2018).

2.4.3 Integration Layer

The integration layer combines data from all sources in the data warehouse. This layer primarily contains two types of data: spatial and non-spatial (Bustamante, Sebastia and Onaindia, 2020).

2.4.4 Process Layer

This layer is responsible for processing the data and generating insights. The processing layer includes tools for data mining, statistical analysis, and machine learning (Zhu, Tang and Li, 2019).

2.4.5 Visualisation Layer

This layer is responsible for presenting the insights generated by the processing layer in a way that is easy to understand and use. The visualization layer includes tools for creating dashboards, reports, and other visualizations (Zhu *et al.*, 2019). The visualisation layer is the last layer of the architecture that is in charge of providing all information to interested users. Utilises a collection of coordinated technologies to make the various analysis jobs feasible to achieve this goal (Bustamante *et al.*, 2020).

2.5 Benefits of Business Intelligence

An effective BI implementation offers a range of business benefits, such as data sources and integration, data management storage, data analysis, data exploration, visualisation of data, and dashboards (Bobylov, 2023). BI systems combine data from various sources, including databases, data warehouses, and data marts. The data must be transformed and cleaned to assure correctness and consistency as part of the integration decision-making (Ain *et al.*, 2019).

2.6 Dimensions of BI adoption

The BI dimensions encompass a range of critical aspects that significantly impact the successful adoption and implementation of BI systems in organisations, including universities (Mohammad, Al-okaily and Al-majali, 2022). These dimensions, as outlined by Zafary (2020), consist of the organisational component, which examines the following (1) how an organisation's culture, structure, and strategic approach influence

BI adoption; (2) the technological component, which focuses on the tools and infrastructure used for data analysis and reporting; (3) the individual component, which assesses employees' skills, attitudes, and perceptions regarding BI; (4) the data component, emphasizing data quality, accessibility, and governance; (5) the process component, which investigates how BI affects decision-making workflows and processes; (6) the performance component, measuring BI effectiveness through key performance indicators (KPIs); (7) the cultural component, exploring the presence of a data-driven culture within the organisation; (8) the strategic component, aligning BI initiatives with long-term organisational objectives; (9) the user experience component, evaluating the usability and satisfaction of BI tools among users; and (10) the ethical and legal component, addressing considerations related to data ethics and compliance. These dimensions collectively provide a comprehensive framework for evaluating and enhancing BI adoption, particularly within academic institutions like universities. Organisational factors, including culture, structure, and strategy, play a significant role in BI adoption, with cultures that embrace innovation and data-driven decision-making more likely to adopt BI (Ahmed, 2021). Similarly, individual factors, such as employees' beliefs in the value of BI, influence its adoption within organisations (Ain *et al.*, 2019).

2.6.1 Data sources and data integration

Integrating data from multiple sources, analysing it with powerful tools, and presenting it in a visual format help organisations optimise their performance and achieve their goals (Damar, 2022). The relevant data is kept in various internal and external data repositories. These sources may include data warehouses, lakes, clouds, spreadsheets, Customer Relationship Management (CRM) and Enterprise Resource Planning (ERP) systems, social media platforms, among others.

Extracting, transforming and loading (ET) data from these sources into a central repository allows for analysis (Hariharan, 2018). As previously mentioned, data integration is one of the processes for combining data from diverse sources and formats into a uniform and consistent format suitable for analysis. It includes data cleansing, transformation, and harmonisation to ensure the data is correct, complete, and dependable. Data integration is beneficial since it allows for the creation of an exhaustive and reliable visualisation of the organisation's data. a (Souibgui *et al.*, 2019).

2.6.2 Data storage and management

A centralised repository known as a data warehouse is created through data warehousing to handle integrated data for reporting and analysis purposes. Large volumes of data from multiple sources can be stored in a structured and efficient way using a data warehouse. This includes a Data Mart, a subset of a data warehouse that focuses on particular divisions, tasks, or business divisions. As a crucial part of BI, data governance regulates the data through policies, procedures, and controls to guarantee data quality, security, and compliance. Rules, processes, and controls must be established to assure data quality, compliance, and accountability. While data security protects against breaches, unlawful access, and data loss (Brill, 2019).

2.6.3 Data analysis and exploration

Some powerful capabilities that BI systems provide for data analysis include data mining, predictive analytics, and statistical analysis. These tools assist companies in discovering previously undiscovered insights, patterns and trends and make better decisions (Surbakti *et al.*, 2020). BI systems enable organisations to understand their data better, detect trends and patterns, and make decisions (Hamad and Jabbar, 2021)

2.6.4 Data visualisation and dashboards

BI systems provide reporting and dashboard capabilities to enable users to visually view and interact with data. These tools allow users to access the information quickly and easily they need and gain insights into key metrics and trends (Wark, 2022). Visualisation tools provide graphical representations, such as charts, graphs, and maps, to simplify data interpretation and highlight trends, patterns, and insights. Through BI solutions, organisations may also keep track of and manage performance in relation to key performance indicators (KPIs) and other metrics. Businesses can use this data to pinpoint performance issues and take the appropriate action (Cardoso & Su, 2022).

2.7 Decision-Making Process (DMP)

The process of decision-making (DM) is a crucial activity for managers, and its complexity has been on the rise, posing a persistent challenge (Abdelrahman, 2019). In today's digital era, an extensive array of tools is employed to collect data, often monitoring individuals' daily activities. This data is then subjected to algorithms for processing, and the outcomes are leveraged to support or guide decision-making (Newell & Marabelli, 2015). Within the Decision-Making Process (DMP), decision-makers integrate diverse data types, both internal and external, as well as various forms of knowledge, including tacit and explicit knowledge. This knowledge is distributed across the organisation, encompassing individual expertise, insights gained from ongoing practices, collective wisdom, and patterns observed in datasets (Newell & Marabelli, 2015). Knowledge workers and managers engage in continuous DMP across a range of applications, such as product design and strategy development (Abdelrahman, 2019).

The DMP includes four phases, according to Hershauer and Simon, (1978) description intelligence, design, choice, and review. The first stage, the intelligence activity, involves searching for environments requiring decisions. The design activity, which is part of the second phase, involves thinking of, inventing, and analysing possible responses to the conditions that have been established. The third stage, called the choice activity, is choosing specific responses to the observed situations. The review activity, which is the final and fourth phase, entails evaluating prior decisions. The DMP model, as described by Simon (1977), is depicted in figure 2 below.

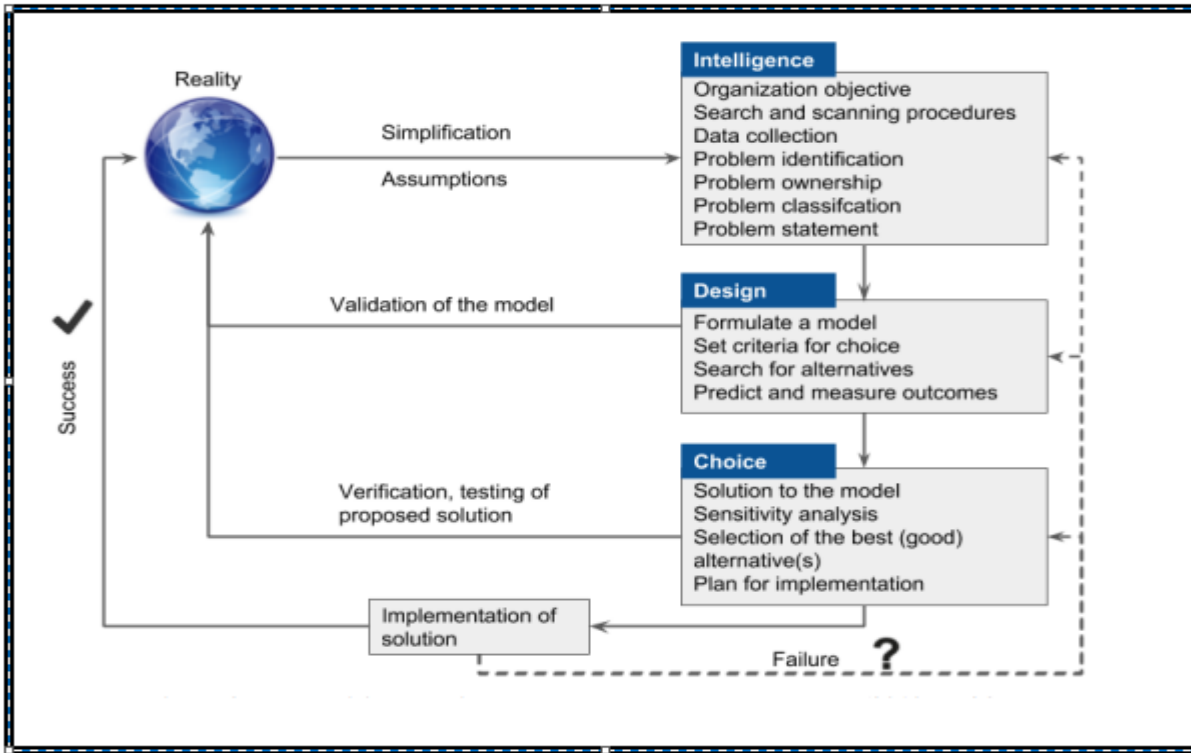


Figure 2: DMP model (Simon 1977)

Huber (1980) later improved the DPM model by adding the implementation and monitoring phases (Lahbi, 2018). The implementation stage entails modifying the chosen solution to a decision-based issue after decisions have been taken, and the implementation may be effective or ineffective. Monitoring is crucial when implementing decisions since it implies checking anything attentively (Lahbi, 2018). Figure 3 below shows this model (Huber,1980).

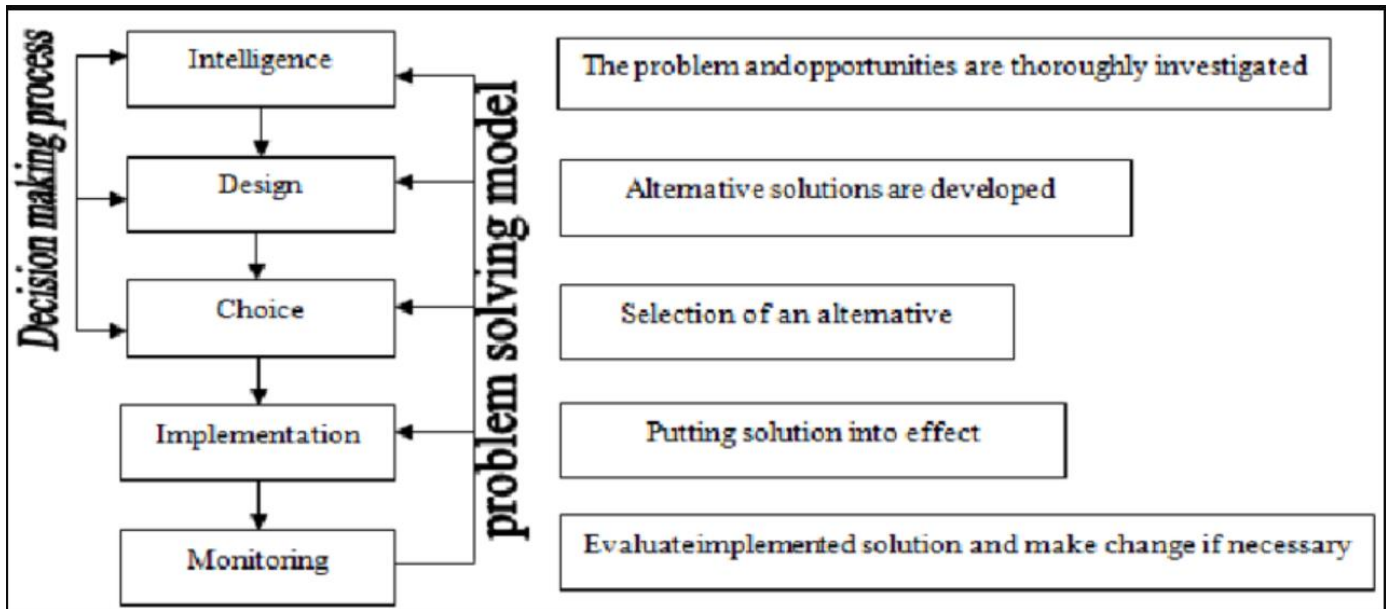


Figure:3 Improved DPM Model (Huber,1980)

2.7.1 Decision Support Systems (DSS)

Interactive systems known as Decision Support Systems (DSS) are designed to aid higher-level decision-making within organisations. They fall within the realm of information systems (IS) primarily focused on providing decision-makers with timely and accurate information, models, and analytical tools to facilitate effective decision-making (Alasiri *et al.*, 2020). Serving as interfaces between various information sources, DSSs consolidate data from databases, spreadsheets, and external systems. Subsequently, they apply analytical techniques to generate valuable insights and recommendations, ultimately assisting individuals or organisations in making sound decisions (Toic *et al.*, 2022). However, it is important to highlight that certain individuals argue that the field of DSS has diminished in significance and relevance, as it has been overtaken by emerging domains such as BI Analytics (BI&A), and Big Data, which offer improved decision-making capabilities (Phillips-Wren *et al.*, 2021).

DSSs are well-established information systems primarily focused on data-driven decision-making. BI often serves as an overarching term encompassing large-scale DSS implementations within organisations. BI functions as a DSS that provides insights and analysis derived from data to support organisational decision-making processes. In certain contexts, BI and DSS are used interchangeably, signifying tools employed

across various industries to collect information and data from diverse sources, analyse them from different angles, and facilitate effective and accurate decision-making (Alasiri & Salameh, 2020). These systems possess the capacity to seamlessly integrate with various other systems and data sources within an organisation, including Enterprise Resource Planning (ERP) systems and Customer Relationship Management (CRM) systems. This integration allows for comprehensive data analysis and decision-making based on current and pertinent information. These systems offer tools and models that assist decision-makers in analysing complex data and arriving at well-informed conclusions, often utilising machine learning and artificial intelligence techniques to identify patterns and trends. Predictive analytics within DSSs employ machine learning algorithms and statistical models to forecast future trends and detect potential opportunities and threats (Alasiri & Salameh, 2020). DSSs find applications across various domains, including universities, marketing, finance, and supply chain management, where they enhance productivity, reduce costs, and help organisations achieve their strategic objectives by providing insights and recommendations, leveraging techniques such as artificial intelligence, machine learning, and statistical analysis (Basile *et al.*, 2023).

Integrated information produced by BI systems significantly contributes to the processes of planning and decision-making. The field of information systems (IS) has witnessed the emergence of various specialised approaches, including management information systems (MIS), decision support systems (DSS), enterprise systems (ES), and executive information systems (EIS) (Tripathi *et al.*, 2020). These distinct approaches cater to specific information needs and serve various facets of organisational decision-making. EIS data was historically used by executives and managers to inform their decision-making. However, because they were not directly linked to the main databases, these EIS dashboards necessitated manual updates. DSSs also demanded significant manual input from individuals and departments, making them unsustainable (Kaur & Baghla, 2022). A BI system serves as a decision support system that enables organisations to extract business value from data Jooste,(2022). Table 1 below provides an overview of DSS.

TABLE 1: Decision Support System (DSS) Jooste (2022)

Decision Support System (DSS) Field	Description
Personal Decision Support Systems (PDSS)	These are miniature systems designed to help one manager at a time or a limited group in making specific decisions.
Group Support Systems (GSS)	Makes use of a combination of technology for interaction and decision-making support to promote efficient teamwork among persons.
Negotiation Support Systems (NSS)	Primarily geared toward assisting groups engaged in negotiations, helping parties with opposing interests reach agreements.
Intelligent Decision Support Systems (IDSS)	These systems incorporate artificial intelligence techniques to enhance decision support capabilities.
Data Warehousing (DW)	Provides a comprehensive data infrastructure, often on a large scale, to support decision-making processes.
Knowledge Management Based Decision Support Systems (KMDSS)	These systems make it possible to make decisions by making a simpler process to store, retrieve, transfer, and use knowledge.

2.8 Business intelligence in universities

Universities have been compelled to enhance their operations to meet increasing demands for efficiency while simultaneously upholding their competitiveness and relevance for both staff and students.(Master and Spring, 2018). Due to the quick development of technology and communication, the higher education sector is currently a dynamic and complex environment with increased competition among universities. Master and Spring (2018) argues that for universities to be competitive and explore new chances, they must stay up to date and employ advanced analytical technology, such as data mining tools and BI systems, to make efficient decisions. BI can be applied in various university areas, from student success and retention to financial management and compliance (Persson and Sjöö, 2017).

By leveraging data and analytics, universities can make better decisions, improve their performance, and enhance their overall effectiveness. BI systems can play a vital role in higher education by enabling universities to make data-driven decisions and improve their operations, efficiency, and effectiveness (Arturo *et al.*, 2020).

BI can monitor student progress, identify at-risk students, support research and development, and provide specific support that improves students' performance. Universities can look through information on student retention, yield on admissions, and application rates. By identifying trends, patterns, and possibilities for cost savings, universities can boost their financial performance and ensure long-term viability. Academic institutions may improve performance, optimise operations, and make data-driven choices with the help of BI tools (Abduldaem and Gravell, 2021) . By leveraging the power of data and analytics, universities may become more competitive, better meet the needs of their stakeholders, and achieve their strategic goals. Universities can improve their competitiveness, better serve their stakeholders' requirements, and accomplish their strategic objectives (Boulila *et al.*, 2018) .

BI is a valuable tool for academic institutions as it enables them to make data-driven decisions, monitor student progress, identify at-risk students, support research and development, and provide specific support that improves students' performance (Boulila *et al.*, 2018). Academic staff can use BI to identify patterns and predictions indicating future trends, enhance evaluation procedures, and assist students in identifying areas that require development or specialization to accomplish their educational objectives more rapidly (Abduldaem and Gravell, 2021) .

By leveraging the power of BI , universities may become more competitive, better meet the needs of their stakeholders, and achieve their strategic goals (Boulila *et al.*, 2018). On the other hand, administrators can monitor performance and trends using business data, identify problems as they arise, and make educated decisions regarding staffing and spending. According to Rippa & Secundo (2019), by developing user-friendly reports that are simple to obtain, university support personnel or administrators can use BI to detect problems and troubleshoot them quickly.

2.9 Usage of BI Technology in Universities

BI supports universities by providing interactive dashboards and visualizations that present essential data and metrics in a clear and user-friendly format. This functionality allows university administrators and stakeholders to quickly grasp data trends and patterns, facilitating well-informed decision-making. BI can assist universities in ensuring compliance with regulatory requirements and accreditation standards by offering accurate and timely data on key performance indicators. These data enable universities to demonstrate their compliance and commitment to continuous improvement (Sharma & Joshi, 2022).

Additionally, BI technology equips universities with reliable tools for data management, key performance indicator analysis, and informed decision-making. By leveraging the capabilities of data and analytics, universities can optimize their operations, enhance competitiveness, and better serve their stakeholders (Caseiro & Coelho, 2019). Indeed, beyond academia, numerous businesses harness BI technologies to monitor customer performance and trends, enhancing the efficiency of their decision-making processes. Almost all major organisations utilise some form of BI. When it comes to higher education institutions, the integration of BI technology offers specific benefits such as enhanced database systems and specialized search engines, designed to meet the distinct needs of academic activities (Duan *et al.*, 2020).

2.10 Theoretical models for evaluating BI

Several comprehensive theoretical frameworks in the field of information systems (IS) can be employed to assess the fitness of BI systems. These methodologies provide structured means for examining the utility, effectiveness, and impact of BI systems on organisational decision-making processes (Ma *et al.*, 2019).

2.10.1 Delone and Mclean IS success model

The D&M model, introduced by DeLone and McLean (1992), serves as a comprehensive framework for evaluating the effectiveness of an Information System (IS). The model identifies six critical factors: system quality, information quality, service quality, usage, user satisfaction, and net benefits. These elements collectively address both the technical performance of the system and the user's level of satisfaction and interaction (Omotayo & Haliru, 2020). The model evaluates technical success, where information quality measures semantic success, and usage contributes to user satisfaction at an individual level. In a related study, the D&M model (2003) was applied to assess the effectiveness of Business Intelligence Systems (BIS) (Andresile *et al.*, 2022). The components of the D&M model are visually presented in figure 4.

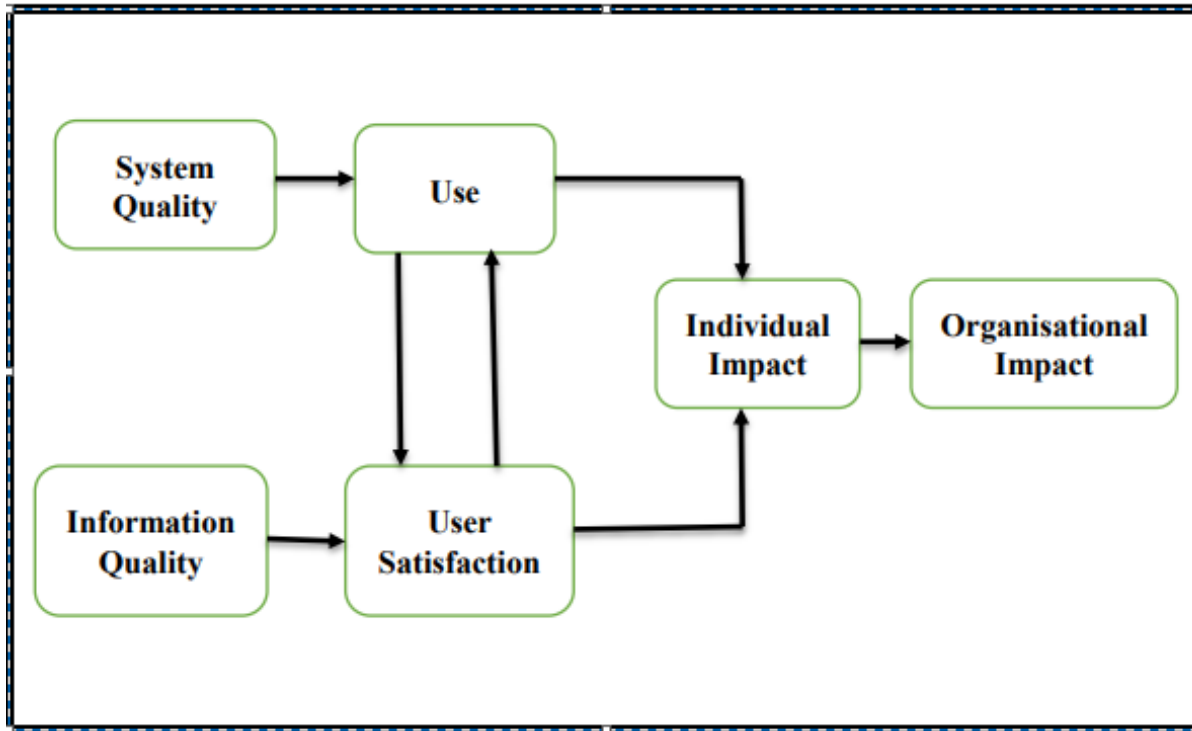


Figure 4: Delone & Mclean's IS Success Model (Alshibly, 2020)

2.10.2 Seddon's IS Success Model Partial

The key differences between Seddon's model and DeLone and McLean's model, as emphasised by Özkan (2015), primarily revolve around the definition and role of IS Use. The Seddon success model, as depicted in Figure 5 below, consists of several categories for assessing information systems success, including system quality, information quality, perceived usefulness and user satisfaction (Mkhonto, 2020). IS usage is viewed as a behaviour rather than a direct measure of IS success. This particular interpretation of IS use suggests that it is considered an outcome resulting from IS success, rather than being an inherent component of success itself.

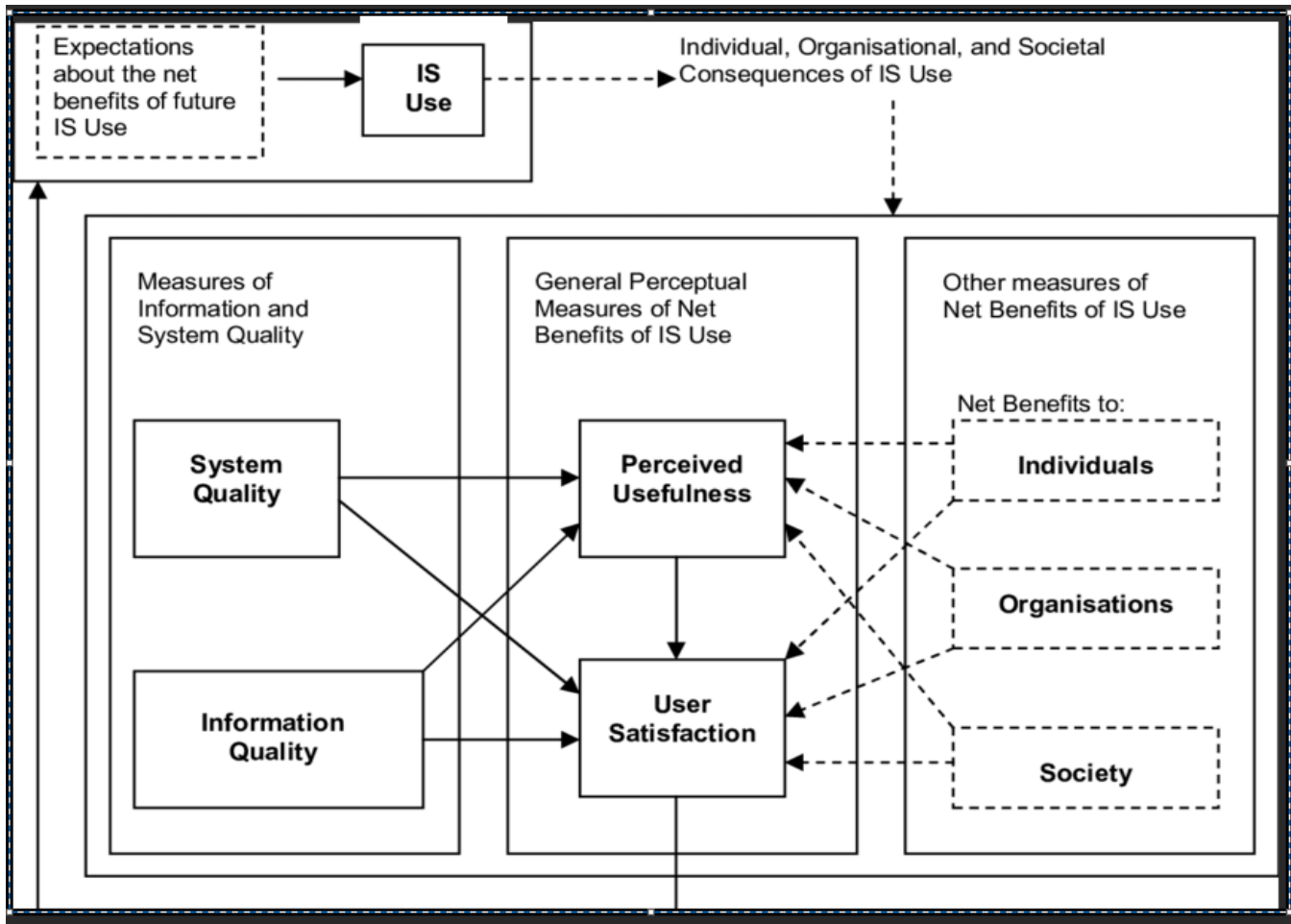


Figure 5: Seddon's Model of IS Success (Özkan, 2015)

2.11 Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) is a theoretical framework that explains and predicts how individuals adopt and use technology. TAM proposes that users' intentions to use a technology depend on two key factors: (1) perceived usefulness (PU), which refers to the extent to which users believe a technology will improve their job performance or simplify their tasks, and (2) perceived ease of use (PEOU), which pertains to users' perception of how user-friendly and learnable a technology is (Al-Emran, 2021).

TAM can be used to assess the acceptance and adoption of BI systems by examining user sentiments regarding a system's utility and ease of use. TAM has been expanded over time by scholars to include

additional elements such as subjective norms, facilitating circumstances, and social impact, which enhance its explanatory power across various contexts. These extensions, such as TAM2 and TAM3, provide a comprehensive framework for understanding the dynamics of technology acceptance and adoption. (Rafique *et al.*, 2020). The original TAM model is shown in figure 6 below that shows that several studies have investigated the adoption of BI in companies using the TAM approach, with some authors focusing on the adoption of OLAP. The TAM model is widely applied and adopted in explaining the concept of technology adoption, and it can be used to investigate the adoption of BI systems in companies (Lo Presti *et al.*, 2021).

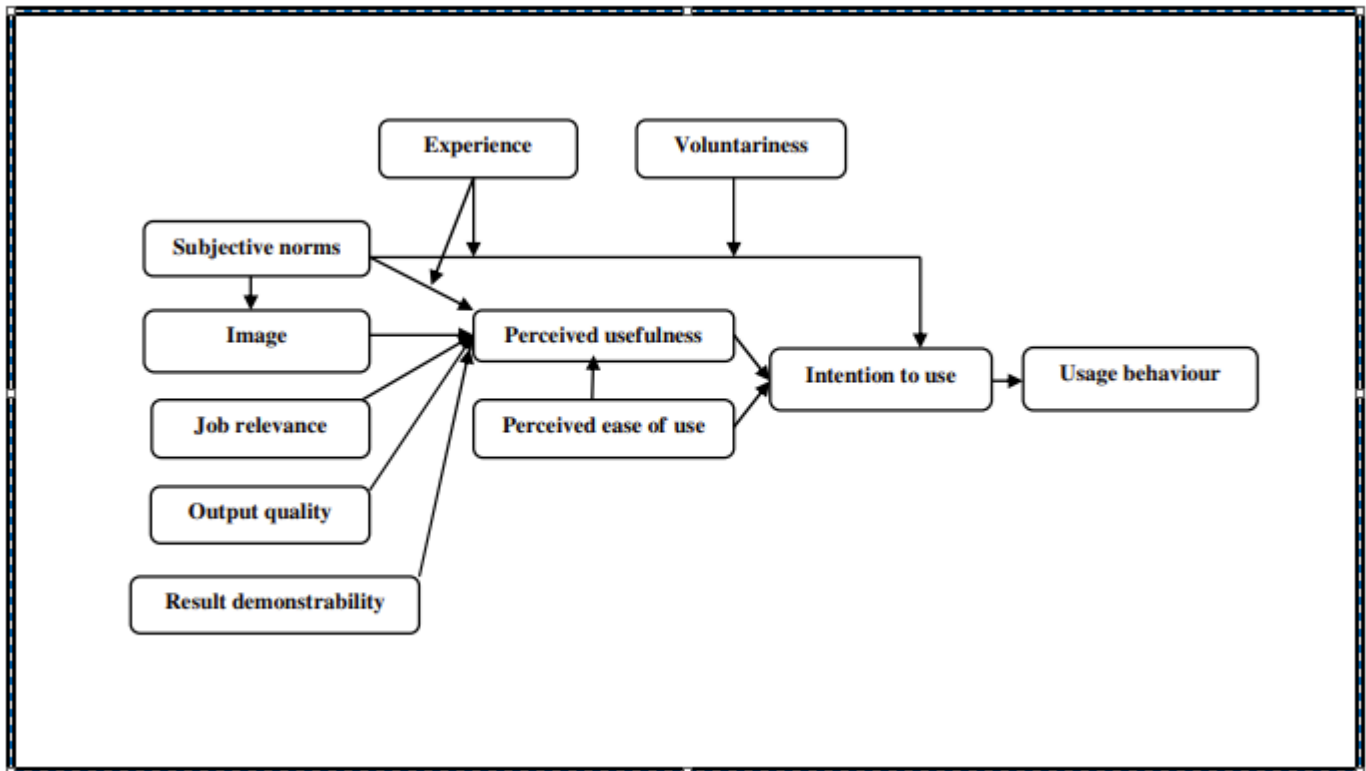


Figure 6: Technology Acceptance Model (Bach, Zoroja and Čeljo, 2017)

2.12 Unified Theory of Acceptance and Use of Technology (UTAT)

The Unified Theory of Acceptance and Use of Technology (UTAUT) is a theoretical model designed to elucidate how users adopt and utilise new technologies. The UTAUT model, initially introduced by Venkatesh *et al.* (2003) has become a prominent framework for understanding and predicting the acceptance

and usage of technology in various contexts, figure 7 below depicts UTAUT that serves as an extension of the Technology Acceptance Model (TAM). The model, extensively applied in diverse studies, including evaluations of e-learning acceptance (Alyoussef, 2023), identifies key factors, performance expectancy (linked to behavioural intention and perceived usefulness), collaborative use of e-learning tools (emphasizing social aspects), effort expectancy (considering ease of use), social influence (external factors and others' influence), and user experience (application features and overall usability). These factors collectively offer a framework to comprehend and predict technology acceptance and usage in various contexts (Alyoussef, 2023).

UTAUT seeks to explain user acceptance of information technology by integrating insights from eight prior models of information technology usage that had proven successful. This model posits that performance expectation, effort expectation, social influence, and facilitating conditions play pivotal roles in influencing users' interest and behaviour when it comes to technology adoption. Additionally, gender, age, experience, and the voluntary nature of use act as moderating factors for these four influencers. Venkateshet *al.*(2003) found a positive correlation between performance expectation, effort expectation, and social influence, driving interest in using information technology. Additionally, they observed a positive relationship between interest in using information technology and supportive conditions (Awanto *et al.*, 2020).

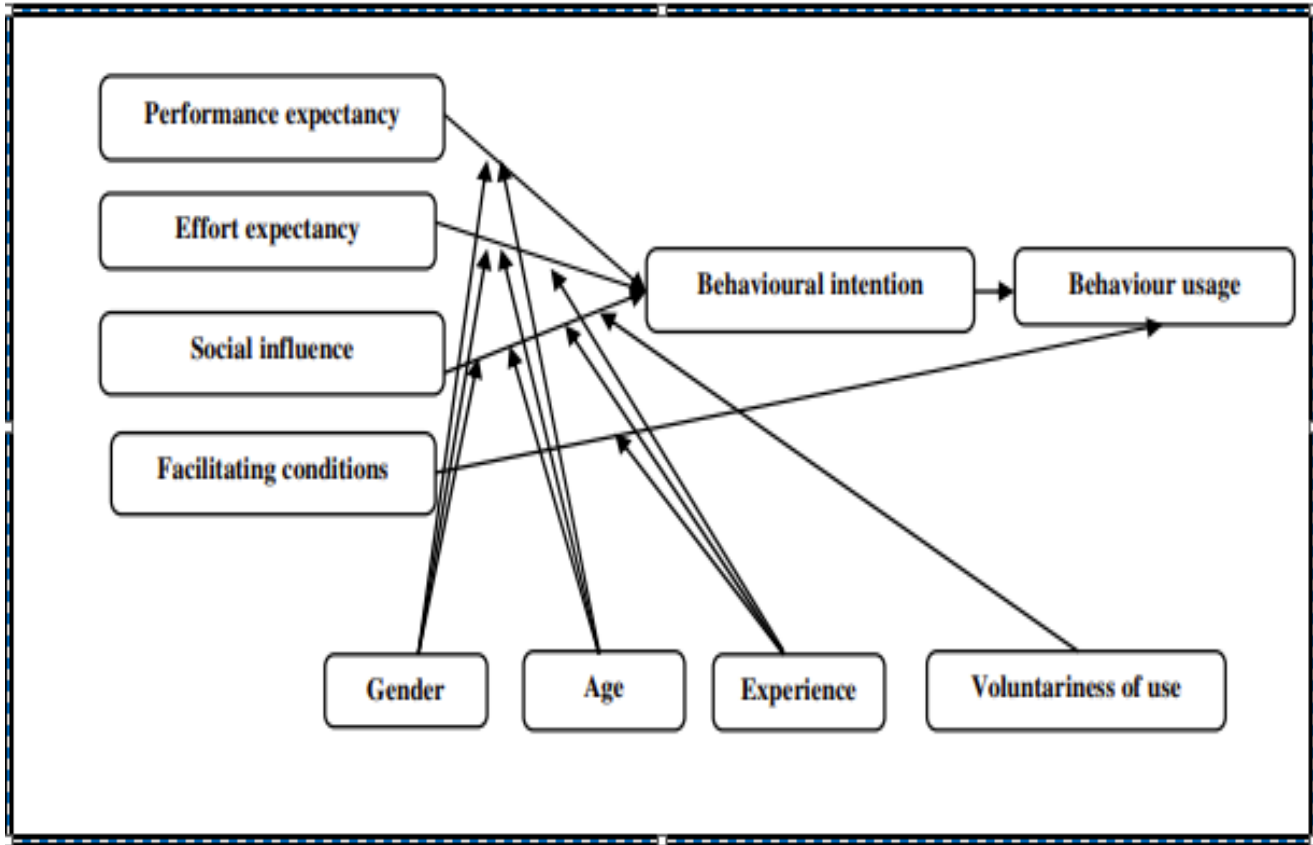


Figure 7: UTAUT Model (Venkatesh et al., 2003)

2.13 Business Intelligence Maturity Model (BIMM)

The Business Intelligence Maturity Model (BIMM) is a framework designed to evaluate an organisation's maturity in adopting and utilising BI capabilities (Cardoso and Su, 2022). The BIMM comprises three levels: Strategic, Management, and Operational, representing different degrees of BI integration and sophistication within the organisation (Hutama *et al.*, 2023). As an organisation progresses through these levels, it enhances its ability to leverage data and analytics for informed decision-making and strategic planning. The model assesses BI capabilities across five stages: Individual Information, Information Islands, Information Integration, Information Intelligence, and Enterprise Information Management (Hutama, Hidayanto and Suryono, 2023).

Figure 8, below from Dinter (2012) illustrates the BIMM levels and the five stages where BI capabilities are assessed. It provides a structured approach to assess and improve an organisation's BI capabilities,

ultimately making it more data-driven and competitive. Therefore, the BIMM evaluates how effectively a company utilizes BI technologies to support decision-making.

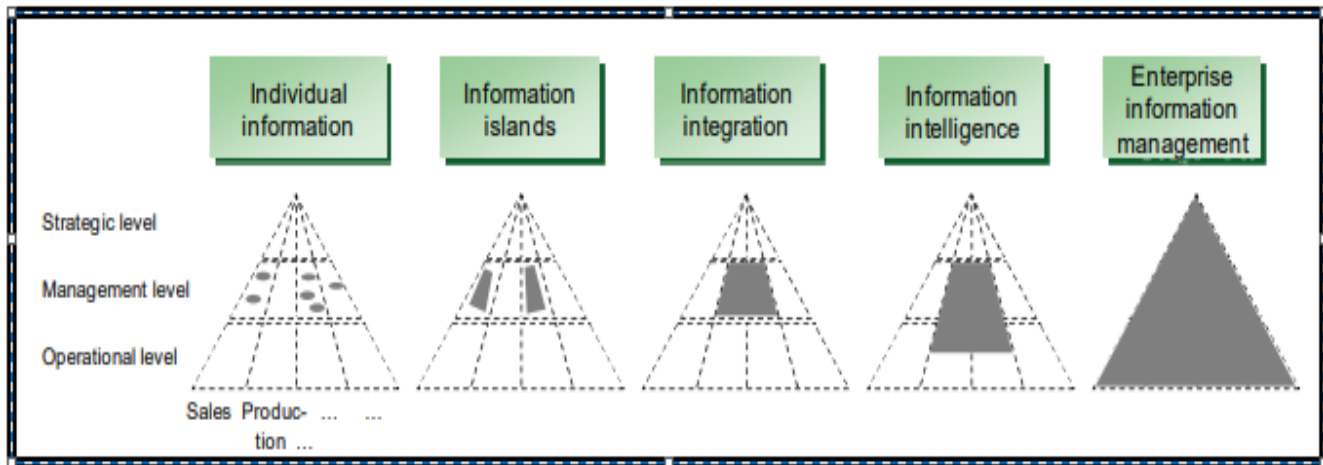


Figure 8: Bim Model (Dinter, 2012)

2.14 Technology Integration Model (TIM)

The creation of the Technology Integration Model (TIM) aimed to address lingering questions about technology usage and to predict its impact. When it comes to factors influencing the sustained use of technology, we can make several predictions. We can expect technology to be used over the long term if it consistently aligns with users' intrinsic and extrinsic motivations and continually enhances an individual's capabilities. This continuous improvement in user experience keeps the user engaged with the technology, as supported by the TIM framework (Shaw *et al.*, 2018).

TIM offers a structured framework for understanding the challenges associated with adopting and integrating technology within an enterprise. TIM helps organisations assess their readiness for technology integration, identify potential obstacles, and determine facilitators. It also aids in developing plans to maximise the effective adoption and utilisation of technology within their specific operational context (Shaw *et al.*, 2018).

2.15 Task-Technology Fit (TTF) Model

The Task-Technology Fit (TTF) Model, originally developed by Goodhue & Thompson (1995), places its emphasis on achieving a seamless alignment between the specific requirements of a task and the features and capabilities of the technology used to carry out that task. This model underscores the significance of a strong correspondence between task demands and the capabilities provided by technology to enhance overall performance and effectiveness (Goodhue & Thompson, 1995). Task-technology fit (TTF) is a theoretical model that suggests that the degree to which a technology (such as a business intelligence system) effectively supports a task is influenced by the degree to which the technology fits the requirements. In the context of quality decision-making, TTF plays a crucial role in determining the effectiveness of a BI system (Wang, *et al.*, 2021).

The TTF theory is notable for being among the first to consider the post-adoption aspects of technology utilisation. The application of this theory is contingent on attitudes, beliefs, and various other factors. For instance, as suggested by Presti *et al.* (2021), theories like TRA (Theory of Reasoned Action) and TPB (Theory of Planned Behaviour) are regarded as valuable tools for understanding technology adoption in the context of better management practices. The advent of digital tools has amplified the demands for effectively managing the TTF model overall (Themistocleous & Papadaki, 2020)

Therefore, the widespread adoption of technology has a major influence on the decisive role played by anticipated technologies up to this point. According to Vendramin *etal.* (2021), the second facet of the TTF theory and model pertains to the technical performance and the alignment of task technology. Numerous associations exist between the technology-fit factor and the adoption of technology, particularly in private organisational settings.

2.15.1 Components of Task-Technology Fit (TTF) Model

As shown in figure 9 below, the Task-Technology Fit (TTF) Model comprises several essential components that facilitate the evaluation of the alignment between the task and technology characteristics. These components provide a framework for assessing the fit between the task and the technology used to support it. The TTF Model provides a structured framework for assessing and improving the fit between task and technology characteristics. It helps organisations make informed decisions regarding technology

selection, implementation strategies, and ongoing improvements to optimise the fit and enhance task performance and decision-making processes.

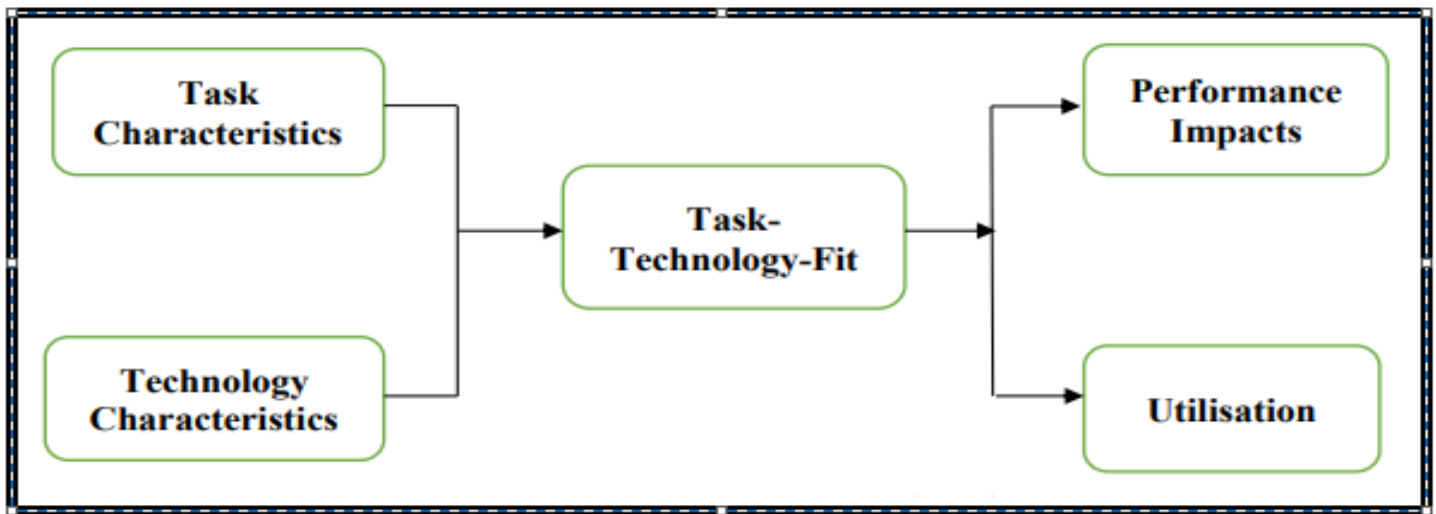


Figure 9: Task Technology Fit (TTF) Model Goodhue and Thompson (1995)

2.15.1.1 Task characteristics

Task characteristics refer to the specific demands, attributes, and features of the task or job being executed. These task characteristics play a pivotal role in evaluating the alignment between the task and the technology employed to facilitate it. This component emphasises the importance of understanding and considering the unique characteristics of the task or set of tasks that the technology solution is intended to support (Alyoussef, 2023). This includes factors such as the task's complexity, interdependence, frequency, structure, pace, and variety. These task characteristics can affect how users interact with the technology solution and can impact the overall effectiveness of the technology (Wang & Lin, 2019).

Task complexity refers to the difficulty, intricacy, or sophistication level involved in performing the task. It considers factors such as the number of steps involved, the amount of information to be processed, the level of expertise required, and the level of problem-solving or decision-making involved (Wang *et al.*, 2020). Complex tasks may require advanced analytical capabilities and sophisticated technology support. Task variety refers to the diversity or range of tasks performed within a particular role or job. Understanding the task characteristics is essential for evaluating the fit between the task and the technology used to support it. It helps select and implement technologies aligning well with the task requirements,

enhancing performance, efficiency, and effectiveness of decision-making. It may involve a high degree of task variety, requiring individuals to perform multiple tasks with different requirements. The variety of tasks influences the flexibility and adaptability of the technology needed to support different task types effectively (Wang *et al.*, 2020).

2.15.1.2 Technology characteristics

Technology characteristics refer to the technology's features, capabilities, and attributes used to support a particular task or job. These technology characteristics are crucial in determining the fit between the technology and the task requirements (Zhang, 2015). System functionality refers to the features and capabilities of the technology system that enable it to perform specific tasks or support specific operations. It includes data collection, storage, processing, analysis, reporting, visualisation, and decision support. The technology should have the necessary functionalities to meet the specific requirements of the task (Jaklič, Grublješić and Popović, 2018). Understanding the technology characteristics helps evaluate the fit between the technology and the task requirements and selecting technologies that effectively support decision-making and task performance (Gengfu, 2019). The concept of task technology fit (TTF) is interdependent on the technology, individual and characteristics of the task.

According to Tamunomiebi and Dagogo (2021), TTF measures how well technology is used within a business. TTF is defined as the degree to which a technology enables a person to carry out their activities. It is accordingly influenced by the relationship between the task's requirements and the technology functions.

2.15.2 Task Technology Fit (TTF) for decision-making

The task-technology fit (TTF) theory explores the connection between digital technology and the tasks it intends to facilitate. TTF is a variance theory describing the interrelationship between three components technology functionality, task requirements, and individual abilities at a specific point in time (Andersone, Nardelli and Ipsen, 2021). The TTF model suggests that a good fit between the technology and the task requirements can increase efficiency, productivity, and user satisfaction .

The Task-Technology Fit (TTF) Model was chosen as the assessment framework for evaluating the suitability of BI tools in supporting decision-making because it provides a structured framework for

gauging and improving the alignment between the specific attributes of the tasks being performed and the technology employed (Omotayo & Haliru, 2020). In the context of this study, the task characteristics of employees utilising the Integrated Tertiary Software (ITS) were assessed to determine how well BI tools fit these tasks. Similarly, the technology characteristics were evaluated to ascertain whether they contribute to decision-making and how well the technology aligns with the tasks at hand.

Task Technology Fit (TTF) for Decision Making refers to the assessment of how well a particular technology, such as BI tools, aligns with and supports the tasks and activities involved in the decision-making process within an organisation (Alyoussef, 2023). It involves evaluating the compatibility and effectiveness of the technology in facilitating decision-making tasks, ensuring that it enhances the quality and efficiency of decision-making processes (Alyoussef, 2023).

Therefore, the fitness of BI for a specific task depends on the alignment of the technology characteristics of the BI system with the task characteristics of the decision-making process. Task Complexity is an important factor that influences BI's fitness for the task (Master and Spring, 2018). Various models and frameworks have been proposed to assess the fit between BI end-users, tasks, and technologies, and to evaluate the impact of BI implementation on decision-making quality (Mazuin *et al.*, 2019).

2.16 Integrated Tertiary Software (ITS)

Integrated Tertiary Software (ITS) is a well-established company founded in 1986, specializing in providing BI systems. CUT relies on ITS as its BI system to support decision-making processes across various academic and administrative functions. Academic support and staff at CUT utilize the online ITS platform to execute tasks that are crucial for informed decision-making. The ITS platform offers a wide range of capabilities, including data integration, data visualization, ad-hoc querying, predictive analytics, and interactive dashboards. These capabilities empower users to collect, analyse, and transform data into valuable insights, driving effective decision-making within the university. By harnessing the power of ITS, CUT enhances its strategies, improves performance, and gains a competitive edge in the academic landscape (Peters *et al.*, 2020).

The ITS system encompasses a suite of online modules known as iEnabler systems, which support essential administrative functions in higher education institutions. These modules include Lecturer Web, Student Selection System, Personnel Web, Finance iEnabler, Request Information, Access Control, and Library

(OPAC) system. These iEnabler systems are fully integrated and web-enabled, providing seamless access to critical information. They enable the extraction of strategic statistical and management data on-demand, facilitating planning and coordination in the decision-making process. ITS has garnered a significant market share in the southern African tertiary education administrative software market, serving over 40 tertiary institutions globally, with 29 of them based in South Africa, ranging from smaller institutions to some of the largest (Mashabela & Pillay, 2017).

2.17 CUT Overview BI tools (Online ITS)

Figure below indicate ITS tools that are being used by CUT and are accessible through cut website

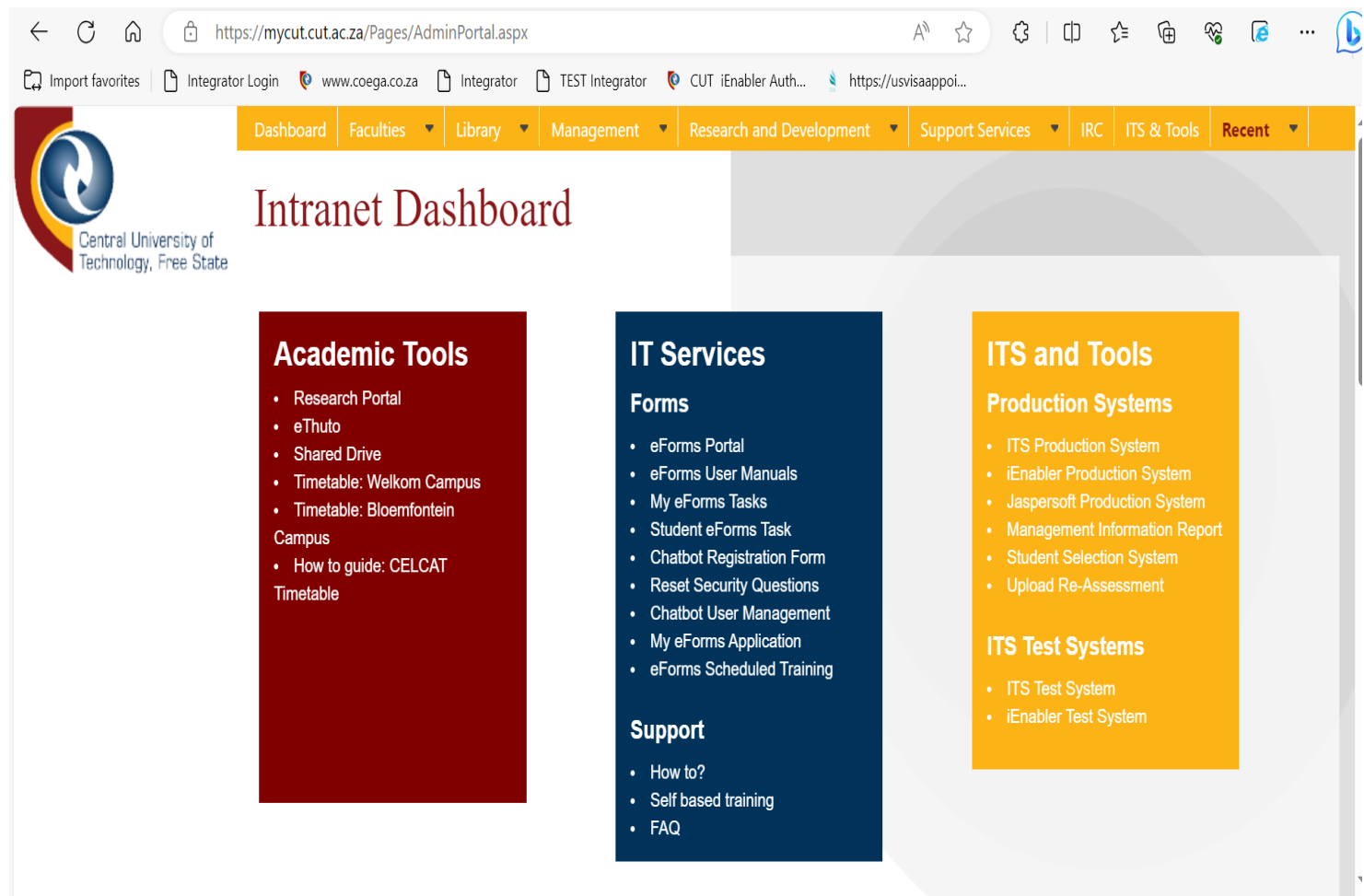


Figure 10: CUT BI Dashboard Online ITS ([cut.ac.za](https://mycut.cut.ac.za))

2.17.1 CUT BI System- Online ITS system dashboard

The Online ITS System is an integral component of the BI system used at CUT. It is accessible through the Online ITS System Dashboard, providing users with a central hub for accessing and managing various BI tools and functionalities. This integration enhances the overall usability and effectiveness of the BI system, allowing users to easily navigate and utilise its features for data analysis and decision-making.

This user-friendly interface of the Online ITS System offers access to a variety of functions and features, integrating subsystems like Student iEnabler, Lecturer I Enabler, Personnel I Enabler, Finance I Enabler, Management Reports, Access Control, and the Library System (OPAC). This dashboard is effectively utilised for tasks related to data analysis, reporting, and decision-making, serving as a vital tool for the university's operational activities. The illustration below depicts the landing page for various ITS online subsystems employed by CUT managers in their decision-making processes.

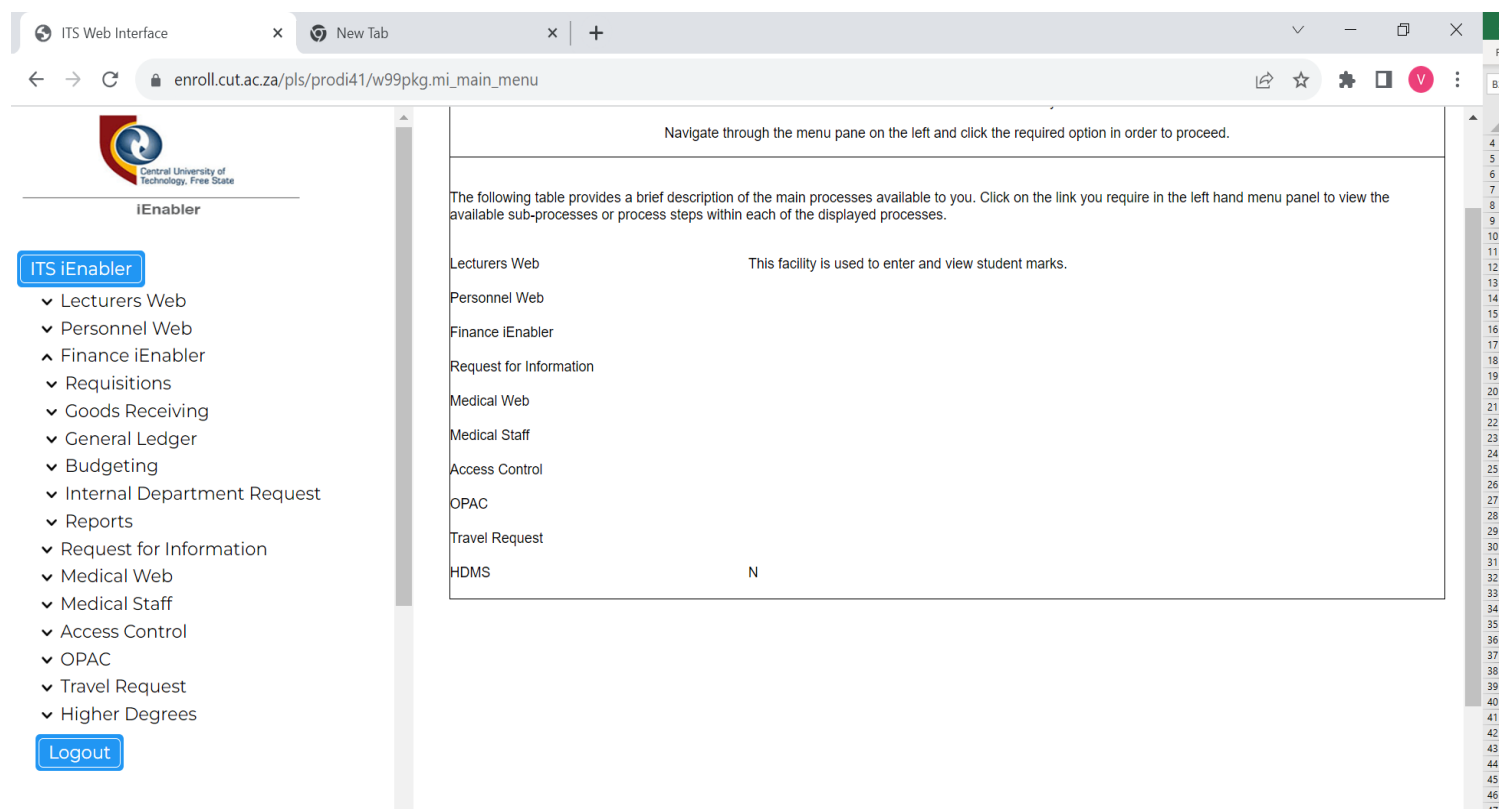


Figure 11: Ienabler Landing Page (ITS web interface (cut.ac.za))

2.17.2 Lecturer Web System

The Lecturer iEnabler web subsystem is a comprehensive digital platform designed to facilitate a broad spectrum of administrative and educational responsibilities for lecturers. Crafted as a specialized platform, the Lecturer iEnabler System aims to streamline various academic and administrative functions. Instructors can conveniently access crucial information such as Class Timetables and Class Lists through this system. Beyond informational access, the platform is equipped to handle a diverse set of administrative tasks. For example, it allows for the input of various academic evaluations, including assignments, examinations, and final grades. The system also features a mechanism for tracking and indicating class attendance, providing a well-rounded tool for educational management. In essence, the Lecturer iEnabler System centralizes essential educational and administrative functions, offering lecturers an efficient means to manage their tasks.

In Figure 12, a variety of functionalities available within the Lecturer Web interface of the BI system is presented. These features serve to centralize various academic and administrative tasks for lecturers, thereby enhancing efficiency and ease of use. By consolidating these features into a single platform, the BI system provides a comprehensive toolset for educational management.

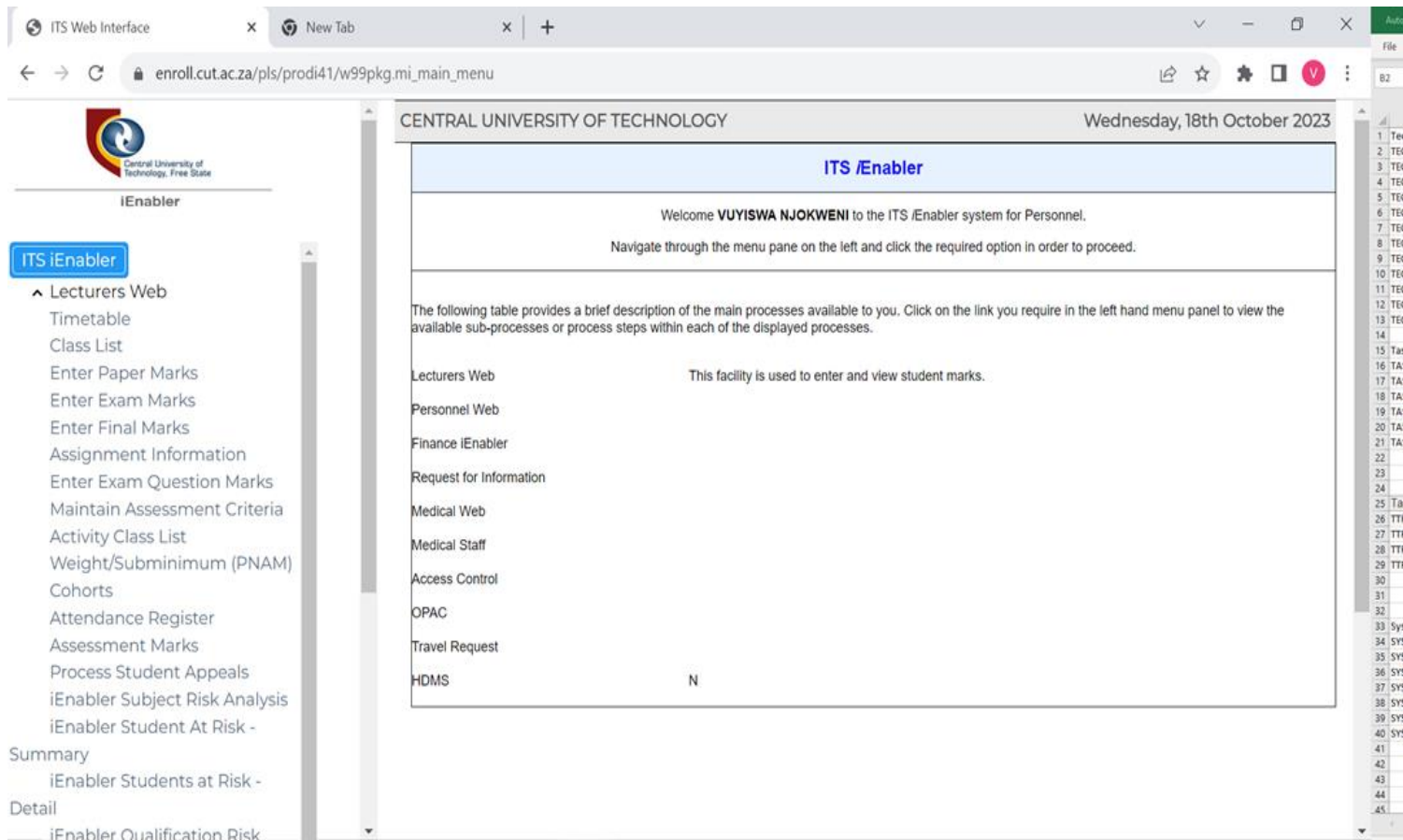


Figure 12: Lecturer Web (cut.ac.za)

2.17.3 BI Systems Used by Managers

The Personnel Web subsystem is employed for leave management, providing a streamlined process for handling employee leaves. The Finance iEnabler is utilized to oversee all procurement transactions, serving as a tool for managers to monitor budgets effectively. The Request for Information subsystem is utilized for requesting reports, facilitating a systematic approach to obtaining necessary information. Additionally, the OPAC subsystem manages library transactions, contributing to the efficient organization of library resources and services.

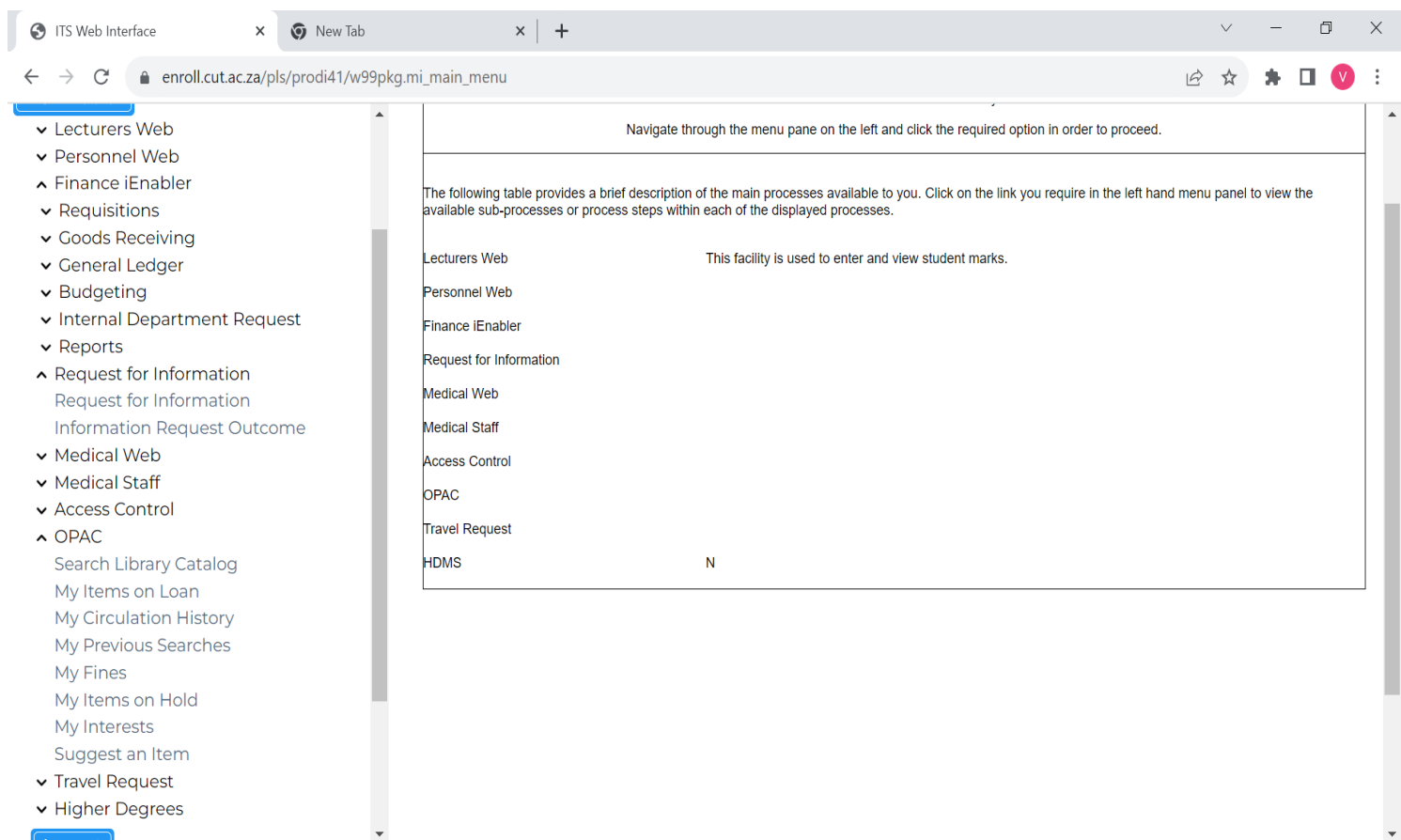


Figure 13: Personnel Web (cut.ac.za)

2.17.4 Student Selection System

The Student Selection System is one of the BI platforms specifically designed to enhance the admissions process. It facilitates the evaluation and selection of prospective students by providing valuable insights and analysis tools. This platform helps streamline the admissions process, making it more efficient and effective for CUT. This system streamlines multiple aspects of the admissions workflow, including application submissions, academic record evaluations, and other essential criteria. It functions as a crucial tool in effectively managing the intake of new students, aligning the university's resources and capacities with the most qualified applicants. In essence, the CUT Student Selection System plays a pivotal role in shaping the academic community within the institution. The figure below illustrates the Student Selection System.

The Student Selection System is designed to manage the process of selecting students for admission to the university. Access to the system is assigned based on job descriptions and qualifications linked to the selectors. Access to the system is controlled using employee personnel and password authentication. This ensures that only authorized personnel with the necessary qualifications can access and use the system to select students for admission.

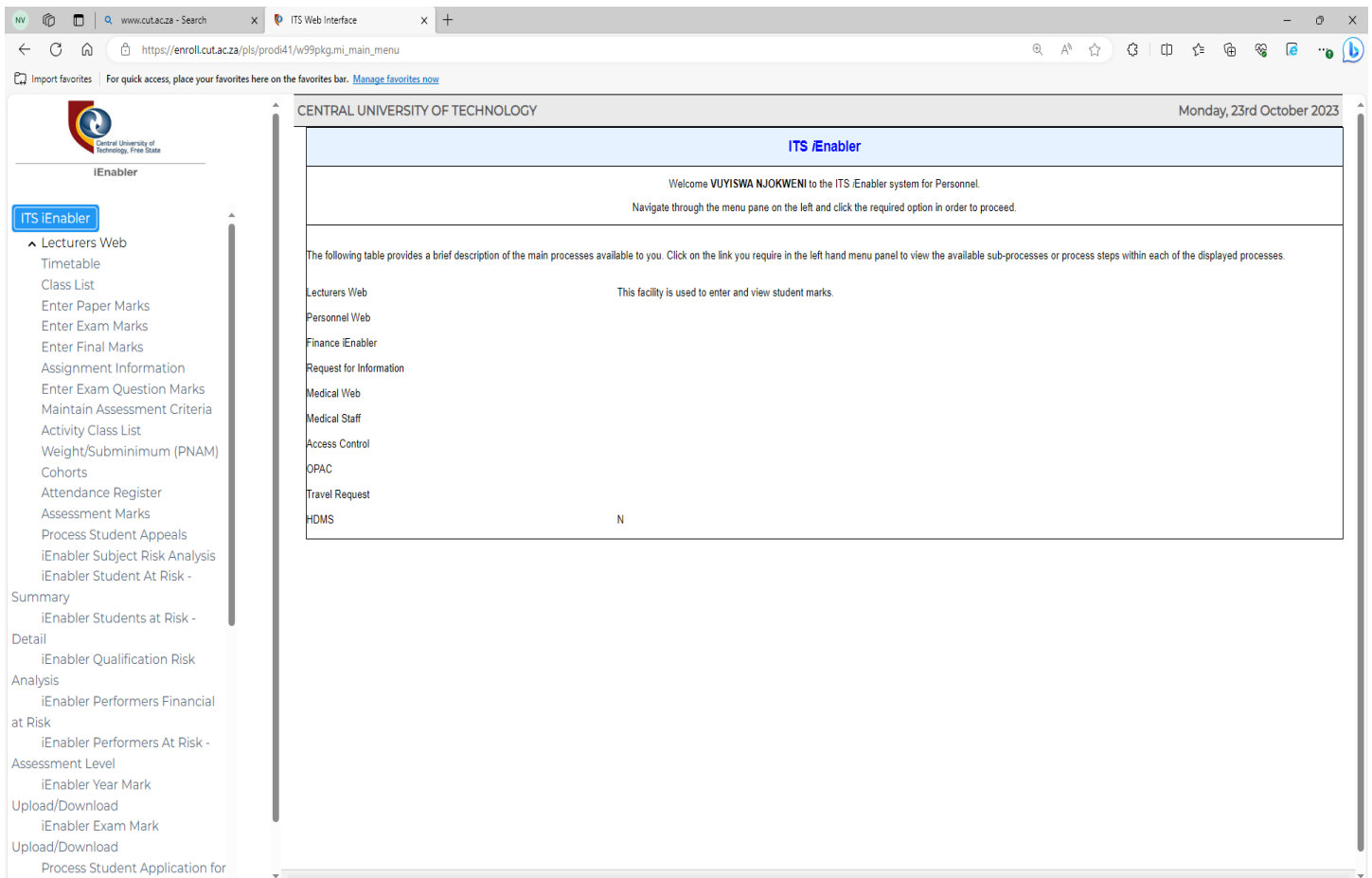


Figure 14: Student Selection System ([cut.ac.za](https://enroll.cut.ac.za))

2.18 About the Central University of Technology, Free State (CUT)

The Central University of Technology, Free State (CUT) is a University of Technology located in Bloemfontein within the Free State province of South Africa. It was established in 1981 under the name "Technikon Free State." However, as part of the South African government's educational restructuring efforts for the new millennium, it was elevated to the status of a university of technology (<https://www.cut.ac.za/cut-at-a-glance>, 2022). CUT holds a prominent position as a higher education institution in the heartland of South Africa. The university operates two campuses, one situated in Bloemfontein, the judicial capital of South Africa, and another in Welkom, strategically located in the heart of the Free State goldfields. These two campuses offer a wide range of educational opportunities across various technological fields, including science, technology, engineering, mathematics (STEM), management sciences, humanities and education (<https://www.cut.ac.za/cut-at-a-glance>, 2022).

The institutional symbol of CUT is a blend of modernity and tradition, where the molecule system within it symbolises technology, innovation, the future, and beyond. CUT recognises a pressing need to assess BI tools fitness in performing its tasks. Universities operate within a complex and rapidly changing environment driven by globalisation and the swift evolution of information technologies, resulting in intensified competition. Universities acknowledge the urgency of conducting an in-depth data analysis to make high-quality decisions in this dynamic landscape.

2.19 Conclusion of the chapter

The chapter offers an extensive review of BI, tracing its history, defining its components, and exploring its utility in diverse contexts. It aims to provide a comprehensive understanding of BI for organisational decision-making. Early BI models were simple statistical tools used for basic data analysis, which have evolved into complex systems capable of real-time analytics and predictive modelling. Various definitions underscore BI's role in helping organisations make informed decisions by analysing structured and unstructured data. The chapter breaks down the architecture of BI into the Data Sources Layer, ETL Integration Layer, and Visualization Layer, each crucial for the effective implementation of BI systems.

BI offers several advantages including enhanced data integration, better data storage and management, simplified data analysis and exploration, and intuitive data visualization and dashboards. BI significantly impacts the Decision-Making Process (DMP) by providing timely, accurate, and relevant data. Decision

Support Systems (DSS) are specialized BI tools that facilitate complex decision-making tasks (Abdelrahman, 2019). The application of BI in universities aids in administrative decision-making, performance tracking, and academic research. Several dimensions affect BI adoption, including organisational readiness, technological capability, and perceived usefulness.

The Theoretical Models for the evaluation of BI offer a comprehensive exploration of frameworks used for assessing the effectiveness and adoption of BI systems. Models such as the Delone and Mclean IS success model, the Technology Acceptance Model (TAM) offer frameworks for assessing the success and adoption of BI tools (Wang *et al.*, 2023). BI systems are evaluated for their fit in meeting specific organisational tasks, providing a measure of their effectiveness and applicability. It examines models ranging from the Delone and Mclean IS Success Model, which evaluates factors such as system quality and user satisfaction, to more specialized frameworks like the Business Intelligence Maturity Model (BIMM), which assesses an organisation's BI capabilities.

The task Technology Fit (TTF) Model emphasises its role in assessing the compatibility between specific decision-making tasks and BI technologies. Integrated Tertiary Software (ITS) are BI solutions that enhance decision-making in tertiary education settings, such as universities. The chapter concludes by introducing the role of BI at CUT, as a case study of BI's utility in higher education settings.

Whilst the chapter provides a comprehensive review, it identifies gaps such as limited research on BI's fitness for tasks in universities and recommends future research to investigate BI adoption in various organisational types and cultures. By synthesizing these elements, the literature review serves as a foundational reference for understanding the complexities and applications of BI in modern organisational structures.

CHAPTER 3: DESIGN AND METHODOLOGICAL APPROACHES

3.1 Overview

This chapter provides a detailed overview of the design and methodological approaches employed in the study. It begins by outlining the chosen research strategy, which is a quantitative method approach to gain a comprehensive understanding of the research questions. The research design is then discussed, focusing on its suitability for addressing the research objectives. The methodology section describes the overall approach to the study, including data collection and analysis methods (Apuke, 2017). The study area is identified, along with the rationale for selecting this particular setting. Data sources are outlined, including primary sources such as surveys, as well as secondary sources such as literature reviews and existing datasets (Mazhar, 2021). Population considerations are addressed, including the identification of the target population and the sampling strategy employed to select participants. Sample size determination is discussed, considering the nature of the research questions and the available resources (Herath and Mittal, 2022). Data collection methods are detailed, including the development of survey instruments. The chapter also discusses the procedures for obtaining informed consent from participants and ensuring confidentiality and anonymity (Mazhar, 2021). Data analysis methods are described, covering quantitative approach. The use of data analysis software is discussed, along with the rationale for its selection. Finally, the chapter evaluates the reliability and validity of the quantitative data, ensuring the integrity and trustworthiness of the study's findings (Taherdoost, 2020).

3.2 Research design

The research strategy plays a pivotal role in providing a structured framework for this study. The research design process holds immense significance as it dictates the approach used to gather pertinent information for the study (Sileyew, 2020). Research design can be perceived as a comprehensive plan aimed at

obtaining answers to the research questions (Sileyew, 2020). Research design serves as a strategic plan that directs the interpretation of data analyses, resulting in the creation of meaningful findings and conclusions. These findings and conclusions then form the basis for recommendations and implications derived from the study's outcomes (Asenahabi, 2019) regards research design as a strategic blueprint that guides the interpretation of data analyses, leading to the generation of meaningful findings and conclusions, which, in turn, serve as the basis for recommendations and implications derived from the study's outcomes. The research design serves as the architectural framework within which the various components of the research project harmonise to address the central research questions (Paledi, 2023). The choice of data sources and the types of data collected are both influenced by the selected research design. Research design can be categorised into three primary groups: quantitative, qualitative, and mixed-method research designs.

The chosen research design for this study is quantitative, as it was deemed the most effective approach to achieve the study's objectives. A quantitative research design revolves around techniques and measurements that yield quantifiable data. In quantitative research, the relationships between variables in the study's objectives are explored to generate data or test hypotheses through various data collection methods (Asenahabi, 2019). Quantitative research can be categorised into non-experimental and experimental research designs (Kumatongo & Musata, 2021). This study adopts a non-experimental design because it is a form of quantitative research that does not involve experimental procedures in data collection. Typically, research studies fall into four common design types: descriptive, explanatory, exploratory, and correlational (Mutambara, 2018).

In line with Sileyew's perspective (2020), the research design plays a crucial role in shaping the study's purpose by influencing decisions regarding data sources and the types of data to be collected. In this quantitative research study, a descriptive design was chosen. This choice was made because the study focuses on collecting data from research participants by asking critical questions and comparing their attitudes on significant matters relevant to the chosen population. The descriptive design aligns with the study's goals as it involves collecting quantitative data that can be quantified along a numerical scale and categorises data, such as gender or patterns within a group (Sileyew, 2020).

By employing a descriptive research design, the study quantified specific observations related to assessing the fitness of BI tools in performing tasks for decision-making and identified relationships between variables. This design selection enables the study to acquire a more profound understanding and enhance the overall strength of the evaluation of BI fitness for task-based decision-making, especially within the framework of CUT.

3.3 Research methodology

Research methodology serves as the comprehensive approach that guides the entire research study process (Sileyew, 2020). It centres around the problems to be investigated within a research study, and the choice of methodology can vary depending on the specific research questions and problems under consideration. One way to conceptualise research methodology is through the analogy of peeling layers of an onion, as (Saunders *et al.* 2019) suggest. The essence of the research is rooted in the research problem, requiring a thorough examination of different factors and considerations before choosing the most appropriate research methodology. This study's research approach highlights the significance of data collection, analysis, and the exploration of key relationships among the studied constructs. In the realm of quantitative research, survey research and experimental research are two commonly utilized methodologies (Ørngreen & Levinsen, 2017).

Among these methodologies, the study opts for the survey research approach. This choice involves using a survey instrument to measure the variables of interest (Asenahabi, 2019). The subsequent sections will provide brief descriptions of the survey strategy and rationale for choosing this methodology over others. The research will explore subjects such as the research population, sample population, and the criteria used to select the sample for this study. It's crucial to emphasize that a population represents a precisely defined group of individuals, events, or entities that are the focus of the investigation and align with the criteria for inclusion in the research sample (Mutambara, 2018).

3.4 The research process

The problem addressed in this study was the assessment of the suitability of BI tools for supporting decision-making processes in South African universities of technology, with a specific focus on the Central University of Technology, Free State (CUT). To tackle this problem, the study conducted a thorough evaluation of BI fitness in performing tasks. The research model was developed through this assessment, incorporating measurement constructs adapted from the Task Technology Fit (TTF) model. These constructs were adjusted as needed to align with the context of the study. The validity and reliability of the research tools employed in this study were comprehensively assessed, primarily relying on the data gathered through online surveys.

Data collection took place at CUT and followed established sampling techniques. Subsequently, the collected data underwent analysis using the partial least squares (PLS) approach, a structural equation modelling (SEM) technique. The results of the analysis were then interpreted and comprehensively documented, enhancing our understanding of the suitability of BI for decision-making in the academic environment.

3.5 Data collection technique

Data collection is a crucial step in any research endeavours, as it involves the gathering of information or data that is pertinent to the research problem under investigation. The choice of data collection method is often contingent upon the specific nature of the research problem and can vary across different academic disciplines. In the context of this study, data collection was centered around academic and support managers who utilised the Integrated Tertiary Software (ITS) online system as a BI tool to facilitate their decision-making responsibilities within CUT

To collect this pertinent data, an online questionnaire was created and administered through the SurveyMonkey platform. This questionnaire was purposefully crafted to directly address the research objectives and to capture the insights, perspectives, and experiences of the designated participants. To ensure maximum participation, the survey link was distributed to the intended respondents via email. The data collection phase spanned a period of six (6) months and was specifically conducted at the Bloemfontein campus of CUT. This extended data collection timeline allowed for a comprehensive and strong gathering of data, ultimately facilitating an in-depth analysis of the suitability of BI tools for supporting decision-making within the academic institution.

3.6 Developing the online questionnaire

An online questionnaire, as part of a survey methodology, entails a series of decision-making processes. These decisions encompass selecting the appropriate research design, formulating research questions, and weighing the advantages and disadvantages associated with using online questionnaires. Additionally, it entails developing and thorough testing of questionnaires to ensure their effectiveness and, ultimately, the collection of data (Ha, 2022). Recognizing the benefits and limitations of online questionnaires plays a crucial role in determining their suitability for a particular research endeavour. It is important to

acknowledge that addressing the challenge of response rates requires careful consideration during the questionnaire design phase, including thorough pretesting. In this context, both the pretest and the actual responses are obtained from the same pool of participants (Saunders *et al.*, 2019).

A well-designed questionnaire is crucial for ensuring the validity and reliability of a survey (Hair *et al.*, 2020). Questionnaires, which consist of predetermined sets of questions distributed to multiple respondents, serve as valuable tools for collecting information, especially when reaching a wide and geographically dispersed audience presents logistical challenges. Like other data collection methods, questionnaires must adhere to ethical and moral principles. Typically, a questionnaire is organised into distinct sections. The initial section aims to capture respondents' demographic characteristics, including gender, age, education, experience, and skills. The next section is usually dedicated to measuring various research variables using multi-item scales. This often involves using Likert-type scales, which incorporate both open-ended and closed-ended questions to collect primary data. Likert scales, in particular, are used to gain deeper insights into respondents' perspectives and opinions. The construction of a questionnaire is a lengthy process, often involving the adaptation of questions from previous studies, such as the Task Technology Fit (TTF) model, to suit the specific research context.

The questionnaire used in the study consists of ten questions and utilises a 5-point Likert scale, allowing respondents to indicate their level of agreement or disagreement, enabling respondents to express their level of agreement or disagreement, ranging from "strongly disagree (1)" to "strongly agree (5)" (Cilliers, 2015)

Cross-check questions are often included within the items to strengthen the questionnaire's reliability and identify any inconsistencies in respondents' responses. The online distribution of the questionnaire through the SurveyMonkey platform facilitates the assessment of its validity. The primary objective of the questionnaire used in this study was to gather data that could be employed to evaluate the suitability of BI tools in performing tasks and supporting effective decision-making at CUT.

3.7 Target population and sample size

A research population typically comprises a significant number of individuals or objects, forming the primary focus of an academic study. This population may also refer to a well-defined group sharing similar

characteristics, with each member possessing some common attribute (Ibrahim & Adamu, 2021). Gift and Obindah (2020) describe the research population as a term denoting a distinct assembly of individuals with shared traits. In this study, the target population consisted of academic managers and support managers at CUT. The quantitative data gathered through an online survey quantitative method was employed for data collection process. The questionnaire was administered to a target population of sixty (60) participants, comprising 40 academic staff (including Deans, Heads of Departments (HODs), and Departmental Managers) and 20 support staff (consisting of senior academic support staff, faculty administrators, and faculty officers).

Conversely, sampling is a method employed to choose a representative subset from a larger population, enabling investigators to draw conclusions about the entire population without conducting a comprehensive census. (Ng'ang'a, 2019). The selected sample primarily consisted of middle-level managers who utilised the online ITS iEnabler as their BI tool for various tasks. This sample included middle-level managers (e.g., Heads of Departments), executive managers (e.g., Deans), assistant registrars, lecturers, faculty administrators, and administration staff. Among the participants, 55% were female, while 45% were male. A significant portion (71%) of academic staff in the sample held postgraduate qualifications. Participants were selected based on specific criteria, including having two (2) to five (5) years of experience in using BI tools, being aged above 46 years, and expressing a willingness to participate in the survey research.

The criteria for selecting participants in this study encompass individuals with a tenure of five (5) to ten (10) years in their current roles, individuals above the age of 46, and those who expressed willingness to partake in the survey research. Flexibility was applied to the participant criteria for the survey portion, enabling a comparison between newcomers to the university who were eager to engage in the research and longstanding employees who may have preferred conventional manual methods over the BI (ITS system) for their tasks. The incorporation of diverse viewpoints contributed to the creation of a purposive sample that was considered sufficient in this study (Gift & Obindah, 2020). This diverse sample was instrumental in drawing conclusions regarding the assessment of BI fitness in supporting decision-making tasks within a university of technology, aligning with the study's objectives.

Table 2: Sample Size Current Job Name Category

Current Job	Current Job Post Name or Category		Sample size percentage
Academic Teaching Support	Lecturer, Senior Lecturer, Departmental Manager, Coordinator	13	32.5%
Senior Academic Teaching Support	Head of Departments (HODs)	12	30%
Executive Academic Teaching Support	Deputy Vice-Chancellor (DVC) Teaching and learning, DVC Research and Faculty Deans.	2	5%
Support staff	Academic Administration support staff, Faculty Assistance Officer, Officer, Personal Assistance, and Secretary	5	12.5%
Senior Support Staff	Faculty Officer, Assistant Registrars, Deputy Directors and Deputy Registrar, and Directors	7	17.5%
Executive Support Staff)	Deputy Vice-Chancellor (DVC) Operations, Senior Directors	2	5%
Skipped		2	

3.8 Research procedures

Prior to the primary data collection phase, a pilot test was conducted with a limited sample from the target population. During this stage, the questionnaire was administered to five participants, including two Associate Professors, two Research Professors, and the Deputy Director of Management Information Systems (MIS). This procedure helped in identifying any questions that were unclear or ambiguous, and necessary adjustments were made to ensure effective communication during the actual data collection phase. The questionnaire explicitly conveyed to respondents that their responses would be used exclusively for research purposes, and their identities would be treated with utmost confidentiality.

3.9 Research model and hypothesis

The research model focuses on assessing the appropriateness of BI tools for decision-making tasks, incorporating constructs such as current position, system usage, task characteristics, and technology

characteristics. Hypotheses were formulated and proposed based on the relationships among these factors, aiming to provide insights into optimizing the adoption and use of BI tools for decision-making.

Each of these relationships is comprehensively explored, discussed, and substantiated using existing literature and theories. Based on these explained relationships among the key factors, a set of hypotheses has been formulated and proposed. Figure 11 provides a visual representation of the proposed research model, offering a clear diagrammatic overview of the relationships between these factors.

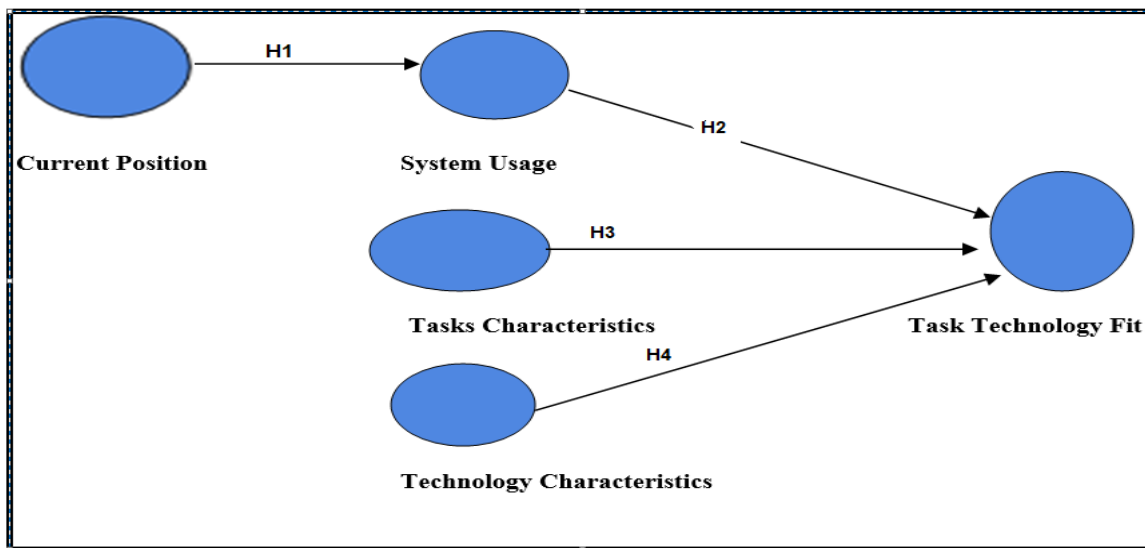


Figure 15: Proposed Research Model

3.9.1 Current position

The construct, serving as a starting point, directly affects system usage, as shown by the H1 arrow. This element encapsulates the specific managerial title or role of the BI system user. The nature and rank of their roles, be it DVC Teaching and Learning, Dean, Head of Department, or Assistant Registrar, play a pivotal role in determining their predilections and necessities for BI tools. Essentially, the kind of decisions that managers have to grapple with is intrinsically tied to their designated roles (Goodhue & Thompson, 1995). Every managerial capacity comes with its distinct responsibilities and decision-making paradigms. Current position predicts the frequency and manner of system usage has significant impact on one's

position, and this, in turn, profoundly impacts the Task Technology fit (Do & Ohlsson, 2018). Therefore, there is a strong correlation between task attributes and the user's current position, indicating that a manager's decision-making tasks are deeply rooted in their designated roles.

Hypothesis 1 (H1). Current Position has a positive influence on System Usage.

3.9.2 System usage

System usage is indicative of the frequency and proficiency with which BI tools are deployed within an entity. As suggested by H2, a surge in system usage can potentially amplify the correlation between the technology and the associated tasks. This is underpinned by the notion that a user's hierarchical role or status can steer their perception of the alignment between the technology and tasks (Vongjaturapat, 2018). In essence, as users engage more deeply with the system, their discernment of its appropriateness might either intensify, or they could unearth discrepancies within the technology System usage posits that the extent to which the system is employed significantly the Task Technology fit. (Pal & Patra &, 2021).

Hypothesis 2 (H2). System Usage has a strong influence on Task Technology Fit.

3.9.3 Task characteristics

Task Characteristics denote the intricacies and nuances of decision-making undertakings within an institution. Task characteristics asserts that the attributes of tasks play a pivotal role in influencing the alignment, or Task Technology fit, of the BI tools used. (Omotayo & Haliru, 2020). Given that managerial responsibilities are intertwined with the functionalities offered by BI tools, H3 underscores the interrelationship between the task's specifics and the suitability of the BI technology in decision-making scenarios (Seqhobane & Koko, 2021)

Hypothesis 3 (H3). Task Characteristics directly influence the Task Technology Fit.

3.9.4 Technology characteristics

Technology Characteristics assess how well decision-making duties and BI tools work together. An ideal alignment would indicate that the BI provides crucial data insights and analytics that are specific to the jobs, supporting effective decision-making (Wang & Lin, 2019) . The technology characteristics may include features and capabilities like user-friendliness, and adaptability of the BI tools in use. H4 might suggest that certain technological features or capabilities improve the alignment of the tool with the decision-making tasks. The alignment between a particular task and its corresponding technology can hinge upon the nature of the task and the features the technology provides. Task Characteristics has strong significant on the dependent variable (Al-Maatouk *et al.*, 2020).

Hypothesis 4 (H4): Technology Characteristics strongly influence the Task Technology Fit

In conclusion the proposed research model in figure 9, is well-structured, capturing critical factors influencing the fitness of BI tools for decision-making tasks (Sari *et al.*, 2018). The hypotheses provide a logical progression and foundation to study the relationships between these factors. The results of testing these hypotheses can offer valuable insights into how to optimise the adoption and use of BI tools for decision-making across various managerial positions. It would be crucial to test these hypotheses using empirical data and statistical methods to confirm the relationships and provide practical recommendations.

3.10 Data analysis methods

In the evaluation of survey data collected via SurveyMonkey for the purpose of assessing the effectiveness of BI in decision-making at the (UT) a thorough methodology was employed. Initially, the collected survey responses were imported into SPSS version 27 for detailed analysis. A detailed examination followed to rectify any gaps or inconsistencies in the data, utilising methods such as data substitution and deletion. Subsequent analysis was conducted in SmartPLS 4, where Partial Least Squares Structural Equation Modeling (PLS-SEM) was applied. This stage served to evaluate the fit of individual constructs in the measurement model, including the testing of the reliability of each item, the internal consistency, as well as

the validity of the measures. The analytical phase enabled the testing of hypotheses within the structural model.

The choice to use Partial Least Squares Structural Equation Modeling (PLS-SEM) in this research is supported by a range of convincing arguments. First, it is highly compatible with initial research aimed at constructing theoretical frameworks, which aligns with the study's goal of evaluating BI within the Task-Technology Fit (TTF) theory. This method is advantageous for probing into theoretical details and for confirming interrelations between different variables.

Second, the research's structural model is complex, with a multitude of constructs, indicators, and interrelationships. PLS-SEM is adept at navigating this complexity effectively. Another advantage of PLS-SEM is its ability to perform reliably even with small sample sizes and intricate models. It is generally recommended that the sample size for PLS should be at least 10 times the highest number of indicators used for any single construct. In this study, the most comprehensive set of indicators pertains to BI fitness and includes 12 questions that test the construct of technology fitness related to BI fitness. In line with a conservative statistical approach, it's advisable to opt for a larger sample size. In this context, the study's sample size of 42 satisfies the minimum criteria, as outlined by Ringle & Wende (2022). Importantly, this sample primarily consists of managers who use the Integrated Tertiary Software (ITS) for their decision-making processes.

The assessment of the outer model included several key evaluations, such as indicator reliability, convergent validity, internal consistency reliability, and discriminant validity. Reliability was assessed using Cronbach's alpha, with values exceeding 0.7 indicating satisfactory reliability. To establish convergent validity, it was necessary for the factor loadings of each construct item to exceed 0.5, composite reliability to surpass 0.5 for each construct, and the average variance extracted (AVE) to exceed 0.5 for each construct. Discriminant validity was verified when two conditions were met: first, the outer loadings for each item within a construct were greater than its cross-loadings on different constructs; second, the square root of the Average Variance Extracted (AVE) for every construct was greater than its correlations with other constructs. The research framework, based on the Task-Technology Fit (TTF) model, included two independent variables: task characteristics and technology characteristics. The dependent variable in this framework was the fit between task and technology, commonly referred to as task-technology fit. Figure 1 illustrates the relationships among these variables within the conceptual model. This conceptual model was substantiated by empirical evidence and existing literature.

3.11 Chapter summary

This chapter serves as a thorough documentation of the research process, providing a step-by-step account of the methodology employed to achieve the study's objectives. Initially, the chapter outlines the research problem and objectives, setting the foundation for the subsequent stages of the study. The chapter is comprehensive, covering a wide range of research aspects, from the research strategy and design to the specific methodology used. The details of the study area clarify the data sources considered crucial for the research. Population considerations are carefully outlined, as is the method for determining the sample size. The data collection methods are examined closely, offering an in-depth understanding of how quantitative data were gathered. The chapter also describes the software tools employed for data analysis. An evaluation of the reliability and validity of the quantitative data is provided, enhancing the credibility of the study's findings. The chapter gives considerable attention to issues of data reliability and offers a detailed reliability analysis. Validity assessment is also given priority, and ethical considerations related to the study are discussed. Additionally, the chapter includes the development of the research model and presents the statistical analyses conducted to assess the model's reliability and validity. Aligning with the study's objectives, a quantitative research approach was predominantly used. It serves as a comprehensive guide, enabling a clear understanding of the research process from its inception through its conclusion, including the rationale and methodologies employed in each stage.

CHAPTER 4: ANALYSIS OF DATA, RESULTS AND DISCUSSION

4.1 Overview

The section offers a structured overview of the results and insights obtained from the survey questionnaire, aligning them with the initial research questions presented in Chapter One. The questionnaire consisted of two parts, Section A, gathered demographic details, such as the age, qualifications, and experience levels of the respondents, while Section B focused on questions directly related to the research objectives. Data analysis was performed using SPSS version 27, facilitating a quantitative assessment of the collected information. To explore the relationships and to address the research objectives, we employed Partial Least

Squares Structural Equation Modeling (PLS-SEM), a prominent statistics tool for analysing multiple variables. PLS-SEM technique was also instrumental in evaluating the reliability and validity of the measurement model (Hair et al., 2020). Background information is also provided, detailing the rate of survey responses as well as demographic information concerning the participants. The chapter concludes by summarizing the research findings and the outcomes of hypothesis testing in relation to the study's objectives.

4.2 Response rate

The response rate serves as a comprehensive instrument for assessing the effectiveness of the survey methodology employed. It provides a holistic view of the level of engagement and the extent of responses received from primary data sources. In the context of the survey, response signifies the percentage of individuals or participants who actively completed the survey or provided their responses relative to the total number of individuals who were initially invited or approached to participate (Luo, 2020). It essentially measures how successful the survey was in eliciting engagement from participants and gathering valuable data. An email link inviting participation in the online survey through SurveyMonkey questionnaires was extended to 60 staff members. Among them, 42 participants successfully completed the online questionnaire. This achievement translates to a response rate of 70%, calculated as $(42/60) * 100$, as explicitly presented in the table below. It's noteworthy that this response rate aligns with the standards of satisfaction outlined in the research of (Miyonga et al., 2018) where a response rate surpassing 40% is considered satisfactory.

Table: 3 Response Rate

Respondents	Distributed	Returned	Percentage
Academic Teaching Support Staff (executives, senior managers, and managers) and Support Staff (executives, senior managers, and managers)	60	42	70.0

4.3 Presentation and Interpretation of Section A: captured demographic information

The collected sample as indicated in Table 3, consisted of 23 (54.76%) females and 19 (45.23 %) males. Most respondents were between 46 and above years old, with 61.90%, followed by those aged between 46 to 45, with 23.81%, and those from 26 to 35 old, with 14.29%. Other 72.93% of the respondents were managers and 27.07% were senior managers. The demographic information also indicated that 35 (88%) of 40 respondents are academic teaching support managers, while 5 (22%) are academic support managers. In addition, the selected sample consisted of staff members who made use of the Integrated Tertiary Software (ITS) online student system (iEnabler) at CUT, including both academic and support units.

Gender	Frequency	% of population	Characteristics
	23	54.8%	Female
	19	45.2%	Male
Age		0.00%	18 to 25
	6	14.3%	26 to 35
	10	23.8%	36 to 45
	26	61.9%	46 and above
Highest Qualification		0.00%	Matric
		0.00%	College Certificate but not Diploma
	1	2.4%	Diploma
	11	26.2%	Degree
	30	71.4%	Postgraduate
Role	12	30.0%	Academic Teaching Support (Lecturer ,Senior Lecturer, Departmental Manager, Coordinator)
	12	30.00%	Senior Academic Teaching Support (HOD)
	2	5.0%	Executive Academic Teaching Support (DVC , Dean)
	5	12.5%	Support staff (Academic Admin, Admin Officer, Officer, Personal Assistance, Secretary)
	7	17.5%	Senior Support Staff (Faculty Officer, Assistant Registrar, Deputy Director)
	2	5.00%	Executive Support Staff (DVC, Registrar, Director, Assistant Registrar)
	2	4.2%	Missing System
Job Experience	13	31.0%	Less than 5 years
	9	21.4%	6 to 10 years
	6	14.3%	11 to 15 years
	7	16.7%	16 to 20 years
	4	9.5%	21 to 25 years
	3	7.1%	26 years and above

Table 2:Demographic Information

4.4 Assessing the structured equation modelling analysis

In this study, the validity and reliability were evaluated, and structural equation modelling (SEM) utilising the SmartPLS methodology was used. PLS-SEM analysis has become a common SEM technique in research because it allows for visual representations of links between relevant variables and establishes the causal relationship between our latent variables. (Sujati *et al.*, 2020). The structure model as shown by the SmartPLS program is shown in Figure 12. The method used to conduct PLS-SEM has been altered from (Muthukrishnan *et al.*, 2022). The assessment of the outer (measurement) and structural (inner) models is the first step in the two-phase evaluation of PLS-SEM outcomes.

4.5 Assessing the outer model

Within the PLS-SEM, the measurement model, often referred to as the outer model, plays a pivotal role in illustrating the connection between a construct and the indicator variables that support it. In the context of measurement models, the primary emphasis is on evaluating convergent validity, discriminant validity, and construct reliability. These aspects are critical for gaining insight into how constructs are accurately measured, as well as for guaranteeing their validity and reliability, as highlighted by Hair *et al.* (2017). The evaluation of the measurement model's validity and reliability involves a systematic approach consisting of five key steps: (1) estimating loadings along with their associated p-values; (2) determining indicator reliability; (3) examining internal consistency reliability; (4) calculating the average variance extracted (AVE); and (5) assessing discriminant validity through the Heterotrait-Monotrait Ratio of Correlations (HTMT), as highlighted by Law and Fong (2020). In the outer model of SmartPLS, the numerical values enclosed within circles, as depicted in Figure 12, provide insights into the degree to which the variation of the latent variable is accounted for by other latent variables. The path coefficients, indicated by the numbers on the arrows, indicate the strength of influence that one variable exerts on another. These path coefficients can be ranked to gauge their relative statistical significance based on their weight.

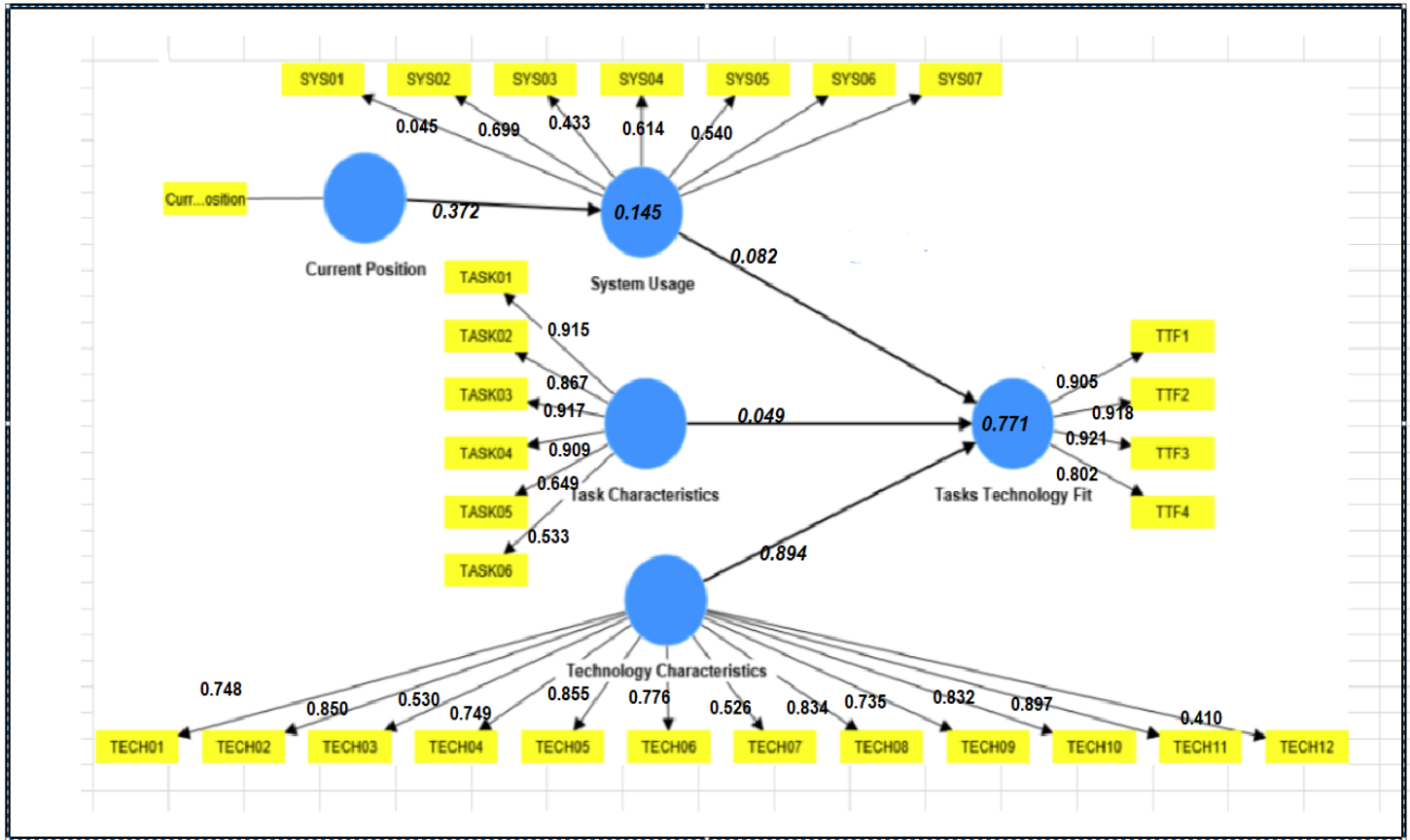


Figure 12: PLS-SEM Model (With Indicators and Latent Variables) Results

The reflective construct's validity is assessed by examining the strength of the relationships between its indicators. For evaluating the reliability of the reflective construct, it is important to consider the loading factor for each indicator. A loading factor is considered reliable when it possesses a standard value of 0.7 or higher, indicating a strong relationship between the construct and its supporting indicator variables. Additionally, the average variance extracted (AVE) should surpass 0.5 to demonstrate that the construct effectively captures the shared variance among its indicators and is a reliable measure. The significant loading factors demonstrate the closeness and interdependence of the variables, providing evidence of their shared meaning (Hair *et al.*, 2019). You can find the results of factor loadings and AVE values for each indicator in table 3 below.

Table 3: Factor Loadings And Ave Values For Each Indicator

Constructs	Code	Measurement Description	Factor Loading	CR	Cronbach's Alpha	AVE
Task Characteristics	TASK01	ITS online helps me to accomplish my tasks more quickly	0.915	0,937	0,713	0,918
	TASK02	Make it easier to complete my tasks	0.867			
	TASK03	It enhances academic support effectiveness	0.917			
	TASK04	Assist to eliminate errors in my work tasks	0.909			
	TASK05	Helps to acquire new skills and knowledge	0.649			
	TASK06	It assists to come up with innovative ideas	0.533			
Task-Technology Fit	TTF1	I am pleased with the quality(accurate, correct, precise) decision made using information provided by the system	0.905	0,931	0,789	0,917
	TTF2	The decision process is efficient (saves time and easier to perform)	0.918			
	TTF3	Indicate individual decision-making satisfaction towards organisational support	0.921			
	TTF4	It helps me to involve my colleagues in making decisions				
Technology Characteristics	TECH01	ITS online system is easy to use	0.802	0,931	0,582	0,917
	TECH02	System is user friendly	0.850			
	TECH03	It is always available	0.530			
	TECH04	ITS online is a reliable system	0.749			
	TECH05	System is useful and relevant to my tasks	0.855			
	TECH06	System is secure	0.776			
	TECH07	Is a stable system	0.526			
	TECH08	It provides accurate information	0.834			
	TECH09	It provides (useful) clear and understandable information	0.735			
	TECH10	Provides information timely	0.832			
	TECH11	It provides usable information that meets user's tasks	0.897			

To enhance the composite reliability score and the average variance extracted (AVE), indicators with outer loadings between 0.40 and 0.70 were removed from the scale (Hair *et al.*, 2020). Indicators with extremely low outer loading values below 0.40 were also eliminated from the construct (Ridwan *et al.*, 2020). All indicators in this analysis met the rule of thumb, as evidenced by their outer loadings being significantly higher than 0.4 and exceeding the AVE value. Therefore, to improve the composite reliability score, all

outer loadings from the System Usage construct and two from the Technology Characteristics construct were removed. The indicators that were eliminated and removed are detailed in Table 5.

As per Gengfu & Chotiyaputta (2019), it is advisable for all loadings to exceed 0.70, and any loadings below 0.4 should be eliminated. Latent variable to account for more than half of the variance in its indicators, the average variance extracted (AVE) should be greater than 0.50, in line with the criteria established by Fornell & Larcker (1981). The values presented in Table 5 demonstrate that the square root of the AVE values surpasses the correlations between constructs (off-diagonal values), signifying the satisfactory discriminant validity of the data, consistent with the guidelines outlined by Gengfu & Chotiyaputta (2019).

Table 4:Removed Outer Loading

Variables/ Constructs	Code	Measurement items	Factor Loading	Information
Current Position				
System Usage	SYS01	Lecturer Web (Class List, Timetable, Paper/Exam Marks, Assessment Marks, Assignment Information, Cohorts, Attendance Register, Student at Risk)	0.045	Outer loading not supporting reliability were removed to increase reliability
	SYS02	Student Selection System (Selection of applicants for prospective and senior students)	0.699	
	SYS03	Personnel Web (Leave System, Personal Maintenance, Staff Development and Training, Supervisors Area, Overtime work)	0.433	
	SYS04	Finance iEnabler (Requisitions, Goods Receiving, General Ledger, Budgeting, Internal Departmental Request)	0.614	
	SYS05	Request Information (Information Request outcome)	0.540	
	SYS06	Access Control (View Your ITS Access Profile)	0.418	
	SYS07	Library (OPAC) system (Search Library Catalog , Items on Loan, Circulation History, Previous Searches)	0.693	
Technology Characteristics	TECH07	Is a stable system	0.526	
	TECH12	System is integrated with other systems	0.410	

4.5.1 Internal consistency reliability

Both the Composite Reliability (CR) and Cronbach's Alpha (α) have been employed to assess Internal Consistency Reliability, as suggested by Law and Fong (2020). A measurement model is considered to possess sufficient internal consistency reliability when the CR for each construct exceeds the threshold of 0.70. Cronbach's alpha reliability coefficient, which typically ranges between 0 and 1, doesn't have a specified lower limit (Hisam *et al.*, 2021). According to the findings presented in Table 6, the composite reliability values for the constructs Task Characteristics, Task Technology Fit, and Technology Characteristics all exceeded 0.7, with a minimum value of 0.932 and a maximum value of 0.944. The only construct that fell below 0.7 in terms of composite reliability was System Usage. Therefore, it can be concluded that all constructs in this study have passed the reliability test and demonstrate consistency.

Table 5: Composite Reliability Value

Variable	Cronbach's alpha (α)	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
System Usage	0,617	0,590	0,695	0,286
Task Characteristics	0,903	0,932	0,918	0,660
Tasks Technology Fit	0,910	0,930	0,937	0,788
Technology Characteristics	0,922	0,944	0,934	0,553

4.5.2 Convergent validity

Convergent validity is the evaluation of how well a measurement aligns with other measurements of the same construct, as outlined by Hair *et al.* (2017). This assessment relies on the Average Variance Extracted (AVE), which quantifies the degree to which the indicators' variability can be attributed to the underlying latent variable. Generally, an AVE value exceeding 0.50 is seen as a strong indicator of good validity, a guideline endorsed by Janadari *et al.* (2016) and supported by the studies of Al-Rahmi *et al.* (2021) and Bagozzi & Yi (1988).

Ab Hamid *et al.* (2017) introduce the Fornell-Larcker criterion as a method to assess discriminant validity. It is based on the idea that the square root of the average variance extracted (AVE) for a latent variable should be greater than the correlations between those latent variables and all other variables. **Error! Reference source not found.** shows that the three constructs, Tasks Characteristics AVE is 0.660, Task Technology Fit AVE is 0.788, and Technology Characteristics AVE is 0.553 with an AVE > 0.50, which shows a good validity, while the construct System Usage AVE < 0.50 is 0.276 shows no validity. A construct with higher Cronbach's alpha may not have good validity if the average variance is low.

4.5.3 Discriminant validity

Discriminant validity testing is a crucial step in instrument development, particularly when dealing with latent variables (Ab Hamid *et al.*, 2017). It refers to the ability of two concepts to exhibit significant conceptual differences. Discriminant validity assesses how effectively a construct can be distinguished from other constructs within a model (Sujati & Gunarhadi, 2020). Ab Hamid *et al.* (2017) argue that discriminant validity is established when a latent variable demonstrates more variation in related indicator variables compared to what it shares with other constructs in the same model. As outlined by Hair, Howard, & Nitzl in 2020, the fourth step of the research process entails the evaluation of discriminant validity. This step is focused on empirically assessing how distinct a particular construct is from other constructs within the structural model. Fornell and Larcker, in their 1981 work, introduced established metrics for this purpose. Their approach suggests that the Average Variance Extracted (AVE) for each construct should be compared to the correlations between that specific construct and all other constructs measured reflectively within the structural model. It is imperative to ensure that the combined variance accounted for by all the constructs in the model does not exceed their respective AVE values. This step is crucial for confirming the distinctiveness and differentiation of the constructs within the research model.

Recent research, as highlighted by Dam & Dam (2021) has raised questions regarding the appropriateness of traditional metrics for evaluating discriminant validity. Henseler and colleagues' work in 2015 has demonstrated that these criteria may not be effective, especially when the indicators loading on constructs show only slight differences. Even when all indicator loadings fall within the range of 0.65 to 0.85, issues related to discriminant validity can still arise. In response to these challenges, Henseler and colleagues (2015) proposed an alternative metric called the heterotrait-monotrait ratio (HTMT) correlation. This metric calculates the mean value of item correlations across different constructs relative to the mean correlations among items measuring the same construct. It offers an alternative approach to assess

discriminant validity, especially in situations where traditional metrics may fall short. High HTMT values indicate a potential issue with discriminant validity. Henseler *et al.* (2015) suggested comparing the HTMT ratio of correlations to a threshold value of 0.85 to assess discriminant validity in variance-based Structural Equation Modeling (SEM), such as partial least squares. The HTMT ratio considers each item as a method. In a simulation study, Hair *et al.* (2019) extended the HTMT method to covariance-based SEM and provided initial supporting evidence.

In Table 6, the HTMT (heterotrait-monotrait ratio) results are presented, with values in bold highlighting potential concerns regarding discriminant validity as per the HTMT criteria. Specifically, the constructs related to system usage, task characteristics, task technology fit, and technology characteristics exhibit problematic HTMT values, indicating the possibility of overlap in the items used to measure these constructs from the respondents' perspective. These findings suggest that examination and refinement of these constructs may be necessary to ensure their distinctiveness in the research context.

Table 6: Heterotrait-Monotrait Ratio (HTMT) – Matrix

	Current Position	System Usage	Task Characteristics	Tasks Technology Fit	Technology Characteristics
Current Position					
System Usage	0,380				
Task Characteristics	0,063	0,307			
Tasks Technology Fit	0,083	0,288	0,291		
Technology Characteristics	0,128	0,511	0,322	0,911	

4.5.3 Model collinearity

Collinearity in a formative measurement model occurs when two or more indicators are highly correlated. To evaluate this indicator collinearity, analysts often rely on the Variance Inflation Factor (VIF), a measure of multicollinearity. As noted by Joseph F. Hair *et al.* in 2019, VIF is commonly used to assess collinearity among indicators within formative constructs. A VIF value exceeding 5 indicates a significant collinearity problem among the indicators measuring formative constructs. However, it's essential to be aware that collinearity issues can emerge even at lower VIF values, such as 3, as mentioned by Purwanto in 2021. Ideally, VIF values should be around 3 or lower. According to Ab Hamid *et al.* in 2017, indicators with insignificant weights should be considered for removal, particularly if their weighting lacks theoretical significance. Indicators with low but significant loadings of 0.50 or less may also be candidates for removal unless there is strong theoretical justification for their inclusion. Table 7, display the VIF values used for collinearity assessment. It is noteworthy that two constructs were identified with VIF values surpassing 5 and were subsequently removed: TASK01, with a VIF value of 5.128, and TECH11, with a VIF value of 5.593. This elimination was conducted as a precautionary measure to address concerns related to collinearity.

Table 7: Model Selection Criteria Joseph F. Hair et al. (2019)

<u>VIF: Technology Characteristics</u>		<u>VIF: Task</u>		<u>VIF: Task Technology Fit</u>		<u>VIF: Current Position & System Usage</u>	
Technology	VIF	Task	VIF	Task Technology Fit	VIF	Job Tittle	VIF
TECH01	3.118	TASK01	5.128	TTF1	3.229	CURRENT POSITION	1.000
TECH02	4.317	TASK02	4.025	TTF2	3.488		
TECH03	2.276	TASK03	4.396	TTF3	3.646	SYSTEM USAGE	VIF
TECH04	3.765	TASK04	4.180	TTF4	2.149	SYS01	1.130
TECH05	4.460	TASK05	2.614			SYS02	1.359
TECH06	4.145	TASK06	2.274			SYS03	1.782
TECH07	2.475					SYS04	1.855
TECH08	4.823					SYS05	1.906
TECH09	3.603					SYS06	1.568
TECH10	3.947					SYS07	1.189
TECH11	5.593						
TECH12	1.638						

4.5.4 The goodness of model fit

The structural model's overall validity, which encompasses both the measurement and structural components, is evaluated using the Goodness of Fit (GoF) index. It offers a standardized way to assess how effectively various models work together. The average value of the R² model is multiplied by the square root of the average communalities index to arrive at the GoF value. According to Purwanto in 2021, GoF values typically vary from 0 to 1, and they can be understood as follows: 0.1 (which means a small GoF), 0.25 (suggesting a moderate GoF), and 0.36 (which means a high GoF).

The SRMR, defined as the difference between observed and model-implied correlations, is considered a good fit when values are below 0.08 (Hu & Bentler, 1998). Henseler et al. (2014) introduced SRMR as a measure for PLS-SEM to avoid model misspecification. In our study, the SRMR value of 0.120 indicates a poor fit.

The Normed Fit Index (NFI) is a measure used to evaluate how closely a model matches the saturated model, acting as a reference point for model fit. Typically, an NFI value above 0.9 indicates a good fit. In

Table 10, the NFI for the saturated model is recorded as 0.430. This value, below the 0.9 threshold, indicates that the model's fit is considered unsatisfactory. The Normed Fit Index (NFI) compares the Chi-square value of the proposed model to a benchmark, with values above 0.9 suggesting an acceptable fit (Bentler & Bonett, 1980). Our NFI value of 0.430 falls below this range. The exact model fit assesses the discrepancy between the empirical covariance matrix and the model's implied covariance matrix. Dijkstra and Henseler (2015a; 2015b) proposed d_LS (squared Euclidean distance) and d_G (geodesic distance) as measures. A good fit is indicated by non-significant differences ($p > 0.05$) between the model-implied and empirical correlation matrices (Henseler et al., 2016).

In our saturated model with no free paths, both the saturated model (measurement) and estimated model (structural) fit values were identical. The SRMR value was 0.030 (> 0.08), the NFI was 0.939 (> 0.90), and both d_ULS and d_G were below the bootstrapped HI 95% quantile, indicating a good fit. Chi-square (χ^2) is used to detect relationships between categorical variables from the same population, comparing observed frequencies to expected frequencies assuming no relationship (Taherdoost, 2020). Smaller chi-square values indicate smaller discrepancies.

Table 10 presents the results indicating that the Chi-square value of 801.263 was statistically significant at a significance level of 0.05. The model's fitness is evaluated using the Standardized Root Mean Square Residual (SRMR), with a threshold of 0.08 indicating excellent model fit (Clay-Williams et al., 2020). The SRMR value for the model in Table 10 is 0.120, above the 0.08 threshold, indicating a well-suited conceptual model for data analysis. Additionally, the assessment of multicollinearity shows that all VIF values are below 5, except for TECH11 (5.593) and TASK01 (5.128), suggesting that the structural model does not exhibit multicollinearity issues (Clay-Williams et al., 2020).

Table 8: Model Fit

	Saturated model
SRMR	0.120
NFI	0.430
D_ULS	6.732
D_G	6.449
Chi-Square	801.263

4.6 Structural (inner) model assessment

The successful outcomes of the measurement model, representing the outer aspect of our research, set the stage for the subsequent phase involving the evaluation of the inner model through Partial Least Squares Structural Equation Modeling (PLS-SEM). This inner model analysis is aimed at uncovering empirical support for the theoretical framework, particularly focusing on the expected relationships between exogenous and endogenous constructs, as outlined by (Al-Sharafi *et al.*, 2023). Our assessment of the structural model comprises three pivotal steps, firstly, assessing the significance and relevance of the relationships within the structural model; secondly, scrutinizing the R-squared values; and thirdly, calculating the effect size (f^2). The results of this assessment, particularly the R-squared values, are provided in Table 12, shedding light on the empirical support for our theoretical model's relationships.

4.6.1 Coefficient of determination (R^2)

The R-squared (R^2) metric serves to quantify the proportion of variance in the dependent variable that can be accounted for by the independent variable. These values play a crucial role in understanding the extent to which exogenous constructs explain the variances observed in endogenous constructs (Tawafak *et al.*, 2023). When assessing the structural model, the R-squared value serves as an indicator of the model's predictive capacity. A commonly followed guideline suggests that R-squared values of 0.75, 0.50, and 0.25 signify a strong, moderate, and weak model, respectively, as outlined by (Sarstedt *et al.*, 2020). Table 11 provides the results of the R-squared values, which are instrumental in evaluating the structural model. This evaluation incorporates both R-squared values and the effect size, f^2 . In accordance with Chin's work

in 1998, R² analysis complements the assessment of f², which measures the change in R² when a specific endogenous construct is removed from the model.

Table 9: R-Square Value

Variable	R-square	R-square adjusted
Tasks Technology Fit	0.771	0.752
Systems Usage	0.145	0.123

The results of data processing in the table above show that the Task Technology Fit (TTF) variable has an R-square value of 0.771, which means that the TTF variable is strong. It can be explained that it predicts the power of the model for BI fitness in supporting decisions with a percentage of 77.1%. At the same time, the system usage variable has an R-square value of 0.145, which means that the weak performance variable can be explained by the construct not predicting power in the mode, with a percentage of 14.5%. Therefore, the structural model (inner model) test results of BI fitness in decision-making variables, the TTF and System Usage variables are included in the strong and weak models' category.

4.6.2 Effective Size F-Square (F²)

F-square measures the importance of changing the R-square value when certain constructs are removed from the model to evaluate whether the eliminated constructs have substantive impacts on endogenous structures (Ridwan *et al.*, 2020). The rule of thumb to assess the f-square value is 0.02, 0.15, and 0.35, which shows that the effect value is small, medium, and large, and the size of the effect with a value less than 0.02 indicates that the variable has no effect (Ridwan *et al.*, 2020). The results of the F-square values are shown below.

Table 10: F² Effect Size

Endogenous Constructs	f square(f ²)	Effect
Current Position -> Systems Usage	0.170	Medium effect
Systems Usage -> Tasks Technology Fit	0.018	Small effect

Tasks Characteristics -> Tasks Technology Fit	0.011	Small effect
Technology Characteristics ->Tasks Technology Fit	2.629	Large effect

4.6.3 Size and significance of the path coefficients

The path coefficient quantifies the strength of the relationship between two latent variables. A path coefficient of 0 signifies no relationship, while a path coefficient of 1 signifies a perfect relationship. These path coefficients are standardized beta coefficients derived from ordinary least squares regression. The significance of path coefficients is determined using the bootstrapping technique, and Table 13 presents the t-statistics indicating perfect relationships between latent variables (Hair, Howard and Nitzl, 2020).

The highest relationship is observed between "Technology Characteristics" and "Tasks Technology Fit" with a coefficient of 0.886, followed by "Current Position" and "Systems Usage" with a coefficient of 0.381. All latent variables exhibit a perfect positive relationship, starting at 1. However, the relationship between "Current Position" and "Systems Usage" is not strong, as the coefficients are below 0.5.(Law and Fong, 2020).

Table 11: Path Coefficients Matrix

	Current Position (CP)	Systems Usage (SYS)	Tasks Characteristics (TC)	Tasks Technology Fit (TTF)	Technology Characteristics (TEC)
Current Position -> Systems Usage		0.381			
Systems Usage -> Tasks Technology Fit				0.070	
Tasks Characteristics -> Tasks Technology Fit				0.053	
Technology Characteristics -> Tasks Technology Fit				0.886	

4.7 Results discussion

4.7.1 Outer Model

The outer model of the SEM was thoroughly assessed to evaluate the relationships between latent constructs and their observed indicators. This measurement model, as described by Hair et al., (2020), plays a crucial role in determining the validity and reliability of the measurement instruments used in the study. Key aspects such as factor loadings, average variance extracted (AVE), and composite reliability were carefully evaluated to ensure that the indicators effectively measured their respective latent constructs. Additionally, the outer model was used to assess the discriminant validity of the measurement instruments, ensuring that each construct was distinct from others in the model. The overall results of the outer model analysis provided strong support for the validity and reliability of the measurement instruments, indicating that they accurately captured the underlying constructs in the SEM (Hair et al., 2020).

Aspect	Discussion
Internal	The internal consistency reliability of the measurement model, as assessed through

Consistency Reliability	Cronbach's alpha, revealed satisfactory results. This indicates that the items measuring each latent construct in the model are internally consistent and reliable. The high Cronbach's alpha values (typically above 0.7) suggest that the items effectively measure the underlying constructs, such as Current Position, System Usage, Task Characteristics, Tasks, Technology Fit, and Technology Characteristics.
Convergent Validity	Convergent validity, as evaluated through factor loadings and composite reliability, demonstrates how items within a construct measure the same underlying concept. In this study, all constructs exhibited strong convergent validity. Factor loadings were well above the recommended threshold of 0.7, indicating that each item contributes significantly to its respective construct. The composite reliability values also surpassed the threshold of 0.7, reinforcing the reliability of the constructs. These results confirm that the measurement model effectively captures the intended constructs.
Discriminant Validity	Discriminant validity assesses whether different constructs are indeed distinct from one another. This is essential to ensure the measurement model can distinguish between related but distinct constructs. Within this research, discriminant validity was demonstrated by comparing the square root of the Average Variance Extracted (AVE) for each construct with the correlations between constructs. The AVE values were consistently higher than the inter-construct correlations, indicating that each construct is distinct. This suggests that the measurement model successfully discriminates between the latent constructs.
Model Collinearity	Collinearity, or multicollinearity, occurs when independent variables in a model are highly correlated, making it difficult to assess their individual effects. This study assessed collinearity through Variance Inflation Factors (VIFs). The VIF values were within an acceptable range, typically below 5, indicating that multicollinearity was not a significant issue. This suggests that the independent variables in the measurement model did not exhibit problematic collinearity.
Goodness of Model Fit	The goodness of model fit is a crucial indicator of how well the measurement model fits the observed data. Several fit indices were employed to evaluate model fit, including the Standardized Root Mean Square Residual (SRMR) and Normed Fit Index (NFI). The results indicate that the model fits well with the data. The SRMR

	was below the recommended threshold of 0.08, suggesting a good fit. However, the NFI value fell below the preferred threshold of 0.90. While this might indicate a slightly less optimal fit, it does not necessarily imply a poor model fit. Overall, the measurement model exhibited a good fit to the data.
Normed Fit Index (NFI)	The Normed Fit Index (NFI) is another measure of model fit. Although it did not reach the recommended threshold of 0.90, it is important to note that various factors, including model complexity and sample size influence NFI values. Given the complexity of the structural equation model and the relatively moderate sample size, the NFI value can still be considered acceptable.

4.7.2 Structural (Inner) Model Assessment

Aspect	Discussion
Coefficient of Determination (R^2)	R-squared (R^2) values provide insights into the extent to which exogenous constructs explain variations in the endogenous constructs. This study assessed the R^2 values for the endogenous constructs, Tasks, Technology Fit and System Usage. Tasks Technology Fit exhibited a notably high R^2 value of 0.771, indicating that the exogenous constructs explain 77.1% of the variance in this construct. This suggests a strong predictive power of the model concerning Tasks Technology Fit. However, System Usage had a lower R^2 value of 0.145, indicating a weaker relationship with the exogenous constructs.
Effective Size F-Square (F^2)	The F-square (f^2) measures the importance of R-squared changes when certain constructs are removed from the model. It helps assess the substantive impact of eliminated constructs on endogenous constructs. The results indicated a medium effect size for the relationship between Current Position and System Usage (0.170) and a small effect size for the relationship between Systems Usage and Tasks Technology Fit (0.018) and between Task Characteristics and Tasks Technology Fit (0.011). In contrast, the effect size for the relationship between Technology Characteristics and Tasks Technology Fit was large (2.629). These findings suggest varying levels of influence of the exogenous constructs on the endogenous

	constructs.
Size and Significance of the Path Coefficients	Path coefficients represent the strength and direction of relationships between latent variables in the structural model. In this study, the path coefficients were examined along with t-statistics to determine their significance. The path from the Current Position to System Usage (H1) was significant ($\beta = 0.381$, $p < 0.005$), indicating that the Current Position has a strong positive impact on System Usage. This suggests that an individual's position significantly influences their system usage for decision-making. The path from Systems Usage to Tasks Technology Fit (H2) was not significant ($\beta = 0.070$, $p > 0.005$), implying that System Usage does not significantly affect Tasks Technology Fit. Similarly, the path from Task Characteristics to Tasks Technology Fit (H3) was not significant ($\beta = 0.053$, $p > 0.005$), suggesting that Task Characteristics do not significantly influence Tasks Technology Fit. However, the path from Technology Characteristics to Tasks Technology Fit (H4) was significant ($\beta = 0.886$, $p > 0.005$), indicating that Technology Characteristics have a strong positive impact on Tasks Technology Fit. This highlights the importance of technology characteristics in determining the fitness of BI for decision-making.

4.8 Hypothesis testing results

The significance of the hypothesis testing is reflected in the path coefficient values. These values indicate the level of significance for the hypothesis testing. In this study, hypothesis testing is conducted at a 5% alpha level, which means that if the t-statistic value exceeds 1.96 or if the probability value at the 5% significance level is less than or equal to 0.05, the hypothesis is accepted. This implies that there is only a 5% probability of errors, and the hypothesis is considered valid (Rani *et al.*, 2023). The path coefficient values are assessed through the t-statistic, which must exceed the critical value from the t-table, typically set at 1.96 for a 5% significance level. When the t-statistic is greater than 1.96 or the probability value is

less than or equal to the level of significance ($\alpha = 5\%$), it can be concluded that the hypothesis is accepted, signifying a significant influence between the tested variables (Rani *et al.*, 2023). The results of the path coefficients test are presented in Table 14, and these values can be interpreted by examining the original sample data to determine the relationship between variables.

Table 12: Path Coefficient

Hypothesis / Variables	Path Coefficient / β	p-value	Decision-making
H1: Current Position -> Systems Usage	0.381 (1 indicated a perfect relationship)	0.003	Assisting
H2: Systems Usage -> Tasks Technology Fit	0.070	0.902	accepted with a t-statistic value > 1.96.
H3: Tasks Characteristics -> Tasks Technology Fit	0.053 (0 indicated no relationship)	0.008	
H4: Technology Characteristics -> Tasks Technology Fit	0.886 (1 indicated a perfect relationship)	0.009	accepted with a t-statistic value > 1.96.

4.8.1 Hypothesis 1: Current Position has a significant impact on Systems Usage

The path H1: Current position -> System usage ($\beta = 0.381$, $p < 0.005$) indicates that the current position positively affects system usage. The study results show that the Current Position had a very strong influence on decision-making. The position is significant in system usage in making decisions. The current position determines the type of system used to make decisions and the system access is granted based on the position.

This hypothesis suggests that an individual's current position within the academic institution significantly influences their usage of BI systems. The path coefficient of 0.381 indicates a strong positive relationship between these variables. In practical terms, this means that individuals in specific roles or positions within the institution are more likely to use BI systems for decision-making. For instance, academic staff members in leadership positions may have greater access to and utilisation of BI tools. This finding underscores the importance of role-based access and highlights the role hierarchy in determining BI usage for decision support.

4.8.2 Hypothesis 2: System usage has no significant impact on Task Technology Fit

The path H2: Systems Usage -> Tasks Technology Fit) ($\beta = 0.070$, $p > 0.005$) indicates that system usage has no significant effect on task technology fit.

This hypothesis examines whether the usage of BI systems significantly impacts the fit between technology and tasks (Tasks Technology Fit, or TTF). However, the path coefficient of 0.070 suggests that system usage has a weak or negligible effect on TTF. This finding challenges the assumption that increased system usage leads to improved alignment between technology and tasks. It implies that using BI systems does not necessarily enhance their suitability for specific decision-related tasks within the academic context.

4.8.3 Hypothesis 3: Task Characteristics have no significant impact on Task Technology Fit

The path H3: Tasks Characteristics -> Tasks Technology Fit): ($\beta = 0.053$, $p > 0.005$) indicates that system usage has no significant effect on task technology fit. Therefore, this is not statistically significant and indicates strong evidence for the null hypothesis.

This hypothesis explores whether task characteristics influence TTF. The path coefficient 0.053 indicates a weak and statistically insignificant relationship between these variables. In other words, the nature of academic tasks or responsibilities does not significantly impact the alignment between technology and tasks. This result suggests that, in the context of the study, task characteristics may not be a primary driver of TTF within the academic institution.

4.8.4 Hypothesis 4: Technology Characteristics have a significant impact on Task Technology Fit

Path H4: Technology Characteristics -> Tasks Technology Fit): ($\beta = 0.0886$, $p > 0.005$) Technology characteristics significantly affect task technology fit for decision-making.

This hypothesis investigates the influence of technology characteristics on TTF. The path coefficient 0.886 signifies a strong and significant positive relationship between these variables. This finding highlights that the features and attributes of the BI technology used within the academic institution substantially affect its alignment with the tasks performed by academic staff. In essence, technology plays a crucial role in enhancing TTF and, subsequently, the fitness of BI for decision-making.

The results derived from Hypotheses 1 and 4 collectively underscore the significance of both the individual's position within the institution (Current Position) and the characteristics of the technology (Technology Characteristics) in shaping the suitability of BI for decision-making. These findings imply that institutions ought to deliberate on providing role-based access to BI systems and investing in technologies that seamlessly align with the specific decision-related tasks carried out within the academic setting. The significance shows a strong positive relationship between Technology Characteristics and Task-Technology-Fit.

The study results show that Technology Characteristics had a very strong influence on Task Technology-Fit. This shows that the assessment of BI fitness in decision-making is determined by task and technology characteristics (Pillai & Sivathanu, 2020). The TTF model's first proposition also states that task and technology characteristics determine the user's evaluation of task-technology fit. The degree to which a technology can assist an individual in decision-making in the current job or tasks is measured by rating four task technology fit dimensions in **Error! Reference source not found.** below with loadings > 0,7 that support decision-making. The Task characteristics were also measured by task interdependence with technology characteristics. Those are the factors that make BI fit to support the decision-making process. This implies that higher Technology Characteristics strongly support the fitness of BI in decision-making. Therefore, increasing Technology Characteristics increases Task-Technology-Fit.

This result suggests that the greater the Technology Characteristics, the more fitness will be achieved from the online ITS system used as BI technologies for decision-making at CUT. Goodhue and Thompson (1995) also supported this result and found support for the link between Technology Characteristics and Task-Technology-Fit. However, they found that Technology Characteristics affect the factors of Task-Technology-Fit differently.

Table 13: Task Technology Fit Measured Dimensions

Variables	Code	Measurement Dimension	Factor Loading	Decision-making
Task-Technology Fit	TTF1	I am pleased with the quality (accurate, correct, precise) decision made using information provided by the system	0.905	The quality of decision-making is positively influenced, leading to more effective and reliable outcomes.
	TTF2	The decision process is efficient (saves time and is easier to perform)	0.918	The efficiency of decision-making is enhanced, allowing for quicker and smoother processes.
	TTF3	Indicate individual decision-making satisfaction towards organisational support	0.921	The system contributes to individual satisfaction with decision-making, potentially improving morale and engagement.
	TTF4	It helps me to involve my colleagues in making decisions	0.802	The system facilitates collaborative decision-making, fostering a more inclusive and team-oriented approach.

The dimensions of Task Technology Fit (TTF1 to TTF4) outlined above offer a detailed insight into how Business Intelligence (BI) technology impacts decision-making. These dimensions cover decision quality, process efficiency, individual satisfaction, and collaboration, all of which play a crucial role in assessing BI fitness. The strong factor loadings (> 0.7) on these dimensions underscore their significance in evaluating the suitability of BI systems.

CHAPTER 5: CONCLUSION AND RECOMMENDATIONS

5.1 Overview

This chapter provides a detailed examination of the study's findings, assessing the extent to which the objectives have been achieved. It includes a summary of the assessment, explanation of the research strategy and a presentation of the findings. The study enriches the theoretical understanding and has practical implications for academic administrators and policymakers. Key findings include the significant effect of aligning technology characteristics with specific tasks on BI fitness for decision-making. The study challenges the belief that increased system usage directly improves decision support. It also emphasizes the importance of employing strong methodologies, such as SEM, for analysing complex BI dynamics in academic environments. The limitations of the study are acknowledged, including the sample size and the cross-sectional nature of the research. Future research recommendations include exploring additional factors influencing BI fitness and conducting comparative and longitudinal studies. The conclusion highlights the importance of task-technology fit in maximising BI potential within academic institutions, recommending ongoing enhancement efforts for BI tools.

5.2 Discussion

The study's findings are carefully examined in this chapter, and we assess the extent to which the objectives of the study have been achieved. Additionally, we give a brief summary of the assessment, explain the research strategy, and present the findings. We emphasise the study's contributions, consider potential directions for future research, provide suggestions and offer concluding thoughts towards the end of this chapter.

The research findings have yielded valuable insights into the intricate dynamics of BI suitability for enhancing decision-making in the unique context of an academic institution, specifically the CUT. These insights not only enrich our theoretical understanding of BI within academia but also carry practical implications for academic administrators and policymakers.

The significant effect of TTF on BI's fitness for decision-making is one important finding from this study. The strong positive correlation between TTF and BI fitness underscores the critical importance of aligning technology characteristics with the specific tasks performed by academic staff. In the context of CUT, where academic and support staff rely on BI systems for decision-making, ensuring that the technology aligns with their specific tasks emerges as a crucial factor. This finding aligns with prior research in the BI field, emphasizing the significance of aligning technology with tasks for effective decision support. Conversely, the study has revealed that System Usage exerts a weaker influence on BI fitness within the academic context. This suggests that simply utilising BI systems does not guarantee their effectiveness in supporting decision-making processes. Factors such as the alignment of technology with tasks hold greater significance in determining BI fitness. This insight challenges the conventional belief that increased system usage directly translates to improved decision support.

The research underscores the importance of employing strong methodologies, specifically Structural Equation Modeling (SEM), for analysing complex BI dynamics within academic environments. SEM facilitated a comprehensive assessment of both the measurement model (outer model) and the structural model (inner model), ensuring the validity and reliability of the study's findings. This methodological rigor represents a valuable contribution to BI research, especially in academic contexts.

5.3 Research Evaluation

The principal aim of this study was to construct a model for assessing the fitness of BI tools in enhancing decision-making processes within South African universities. To accomplish this objective, the study employed the TTF model as its guiding framework to address the research questions. This investigation was conducted within the context of a case study at the Central University of Technology, Free State, in the South African Free State. The study's guiding principles were established in Chapter 1, comprising three research questions and their associated objectives. These objectives were thoughtfully devised to explore various aspects of BI's fitness in supporting decision-making within academic institutions, with a particular focus on CUT. Now, let's assess the degree to which these objectives have been fulfilled:

5.3.1 Technological characteristics of the BI tools commonly used by UoTs

Objective 1: To carry out a detailed analysis of the technological characteristics of the BI tools commonly used by UoTs in South Africa

In the context of higher education, particularly within South African universities of technology (UoTs), Business Intelligence (BI) tools are instrumental in facilitating effective decision-making processes. Objective 1 of this study was motivated by the imperative to comprehend the technological intricacies of these tools to unlock their full potential within institutions. This objective aimed to meticulously dissect the technological attributes of commonly used BI tools in South African UoTs. To achieve this, a meticulously crafted questionnaire was employed, focusing on specific technological characteristics that are pivotal in the decision-making process. These characteristics not only influence the efficiency of the tools but also their adaptability and relevance in the dynamic environment of a UoT. The Integrated Tertiary Software (ITS) stands out as a significant BI system implemented by the Central University of Technology (CUT) to enhance its decision-making processes. The study investigated the key technological attributes of ITS, including usability, availability, reliability, relevance, security, timeliness, accuracy, clarity, and integration. These attributes were thoroughly assessed to determine ITS's effectiveness in supporting decision-making processes within UoTs. The study's conclusion emphasised a strong linkage between the technological characteristics of BI tools and their ability to support the specific tasks and goals of UoTs, highlighting the importance of these tools in the higher education landscape.

5.3.2 Main tasks performed by middle-level and executive managers at UoTs

Objective 2: To identify and characterise the main tasks performed by middle-level and executive managers at UoTs South Africa

In particular, tasks involving student processes and procedures such as student recruitment, enrolment, assessment, and graduation will be analysed. The identified tasks will be subjected to a task-technology-fitness test to determine their fitness for quality decision-making. This research study's critical success

factor is that Task characteristics are Technology characteristics; Task Technology Fit Characteristics positively influence how the task is performed using the BI system for decision-making.

The second objective sought to identify and characterise the primary tasks undertaken by middle-level and executive managers within South African UoTs. The dissertation effectively accomplished this objective by collecting surveys and data from academic teaching and support staff at CUT. The collected data provided insights into these managers' specific roles and responsibilities. By characterizing their tasks, the study contributed to a comprehensive understanding of the decision-making context within the academic institution. The findings from this objective served as a foundation for subsequent analyses.

5.3.3 TTF Model for Assessing (Integrated Tertiary Software) ITS' fitness for quality decision-making at CUT

Objective 3: To apply the Task-Technology-Fit Model to design and evaluate an IS model for assessing ITS' fitness for quality decision-making at the Central University of Technology, Free State (CUT)

This study makes a substantial contribution to the field of information systems (IS) diffusion in several ways. It employs a comprehensive approach by integrating components from both the Task Technology Fit (TTF) model, originally developed by Goodhue (1995), and the Fit-Viability model created by Liang and Wei (2004). The research effectively validates the proposed model and the relationships between key variables, particularly within the specific context of the CUT. Throughout the research process, the variables consistently exhibited a satisfactory level of convergence, validity, and reliability. As a result, this study enhances the existing literature by critically assessing the viability and validity of the TTF model.

The third objective of this study aimed to leverage the TTF Model for the creation and evaluation of an information system (IS) model, specifically focusing on assessing the appropriateness of the Integrated Tertiary Software (ITS) in supporting high-quality decision-making at CUT. This objective was successfully accomplished through the application of structural equation modelling (SEM) techniques. The SEM analysis outcomes provided strong evidence for the validity of the TTF Model in evaluating the alignment of BI within an academic context. The results emphasized the substantial impact of technology characteristics on Task-Technology Fit (TTF) and, consequently, on the suitability of ITS for decision-

making. By attaining this objective, the research has generated a practical IS model that can be effectively utilised to assess and enhance BI systems in similar academic settings.

5.4 Limitations of the study

Similar to other research studies, this study had its share of limitations. One noteworthy limitation is the sample size which consisted of 42 participants, excluding other potential system users. The distribution of the survey was conducted online. Due to the challenges posed by the COVID-19 pandemic during data collection, we faced difficulties in obtaining more responses. Many potential respondents felt overwhelmed and lacked the time to complete the survey, resulting in a relatively small sample size of 42 (Sileyew, 2020). Therefore, while this dissertation has made substantial contributions to the understanding of BI suitability for decision-making in academic institutions, it is crucial to acknowledge these limitations. These limitations present opportunities for other research and help to contextualise the findings of this study.

5.4.1 Single Case Study Focus

The study primarily focused on a single case study, the Central University of Technology, Free State (CUT). While the findings provide valuable insights into this specific institution, they may not be directly generalisable to all South African universities of technology or other types of academic institutions. Future research could encompass a broader range of institutions to validate and extend the current findings.

5.4.2 Sample Size

The study's sample size consisted of 42 academic teaching and support staff from the CUT. While this sample was deemed sufficient for the SEM analysis, it may not fully represent the diverse roles and responsibilities within the institution. Expanding the sample size and diversifying the participant pool could yield more comprehensive results.

5.4.3 Survey-Based Data

This data collection method relied on survey questionnaires that are subject to self-reporting bias. Participants' responses may be influenced by their perceptions and subjective experiences. In future

research initiatives, it would be advantageous to broaden the array of data sources employed, potentially including methods like interviews or direct observations. By doing so, the study could acquire a more comprehensive and well-rounded understanding of the decision-making processes under investigation.

5.4.4 Cross-Sectional Nature

The research in question employed a cross-sectional research design, which essentially means it captured a momentary view of the state of BI fitness at the CUT, a specific academic institution. This approach allowed us to gain insights into BI fitness at a single point in time. However, the statement also highlights the potential advantages of adopting a longitudinal research design instead. Longitudinal studies involve collecting data over an extended period, enabling us to monitor changes and trends in BI adoption and fitness within academic institutions over time.

5.4.5 Generalisability to Other Contexts

While valuable within the context of South African universities of technology, the study's findings may not be directly applicable to institutions in other countries or regions. Differences in institutional structures, cultures and technology adoption rates could impact the relationships identified in this study.

5.4.6 Technology Evolution

BI technology is continuously evolving. The study's analysis of ITS represents a specific moment in time, and subsequent technological advancements may influence the relationships between technological characteristics and BI fitness. Future research should consider the dynamic nature of BI tools.

5.4.7 Measurement Scales

While this study employed established measuring scales, slight variations or adaptations were made to fit the specific context. These modifications may introduce some level of measurement error. Future research could explore the development of context-specific measurement instruments.

5.4.8 Task Complexity

The study characterised tasks primarily based on frequency and criticality. Task complexity, which can impact BI fitness was not explicitly considered. The research could investigate into task complexity's refined aspects and implications.

5.4.9 Conclusion

Despite these limitations, this dissertation establishes a solid groundwork for future research contributions in the field of BI fitness within academic institutions. Acknowledging these constraints, scholars can enhance research methodologies, broaden sample sizes and investigate additional factors, ultimately advancing our comprehension of BI's role in facilitating data-driven decision-making in academia.

5.5 Future work recommendations

For future research, it is recommended to broaden the scope of BI adoption and usage assessment by including a wider range of South African universities that include traditional universities in addition to universities of technology. This expansion should involve the participation of all BI users, not just managers, to provide a more comprehensive understanding of BI fitness for decision-making. Additionally, the impact of different BI systems on decision-making processes should be considered by assessing universities that use various BI systems.

This analysis will offer insights into how system variability influences BI fitness. The future studies should explore deeper into factors influencing BI fitness, such as user training, organizational culture, and data quality, to understand their interplay with Task-Technology Fit (TTF) and System Usage. Comparative studies across academic institutions can provide insights into how contextual factors impact BI fitness, helping to identify best practices. Longitudinal studies tracking the evolution of BI fitness over time can reveal trends and patterns, informing continuous enhancements. Qualitative research methods, such as focus groups and interviews, can strengthen the quantitative results by offering in-depth insights into the opinions and experiences of academic staff regarding BI fitness. Lastly, benchmarking studies comparing BI fitness in academia with other sectors can drive improvements and innovation in BI usage for decision-making.

5.6 Conclusion

This research study highlights the crucial role of the CUT's online Integrated Tertiary Software (ITS) and BI tools in supporting decision-making processes. Task-technology fit (TTF) emerged as a critical factor, emphasising the importance of aligning BI tool capabilities with specific decision-making duties. When the other BI tools seamlessly integrate with the ITS online system, they enhance user experience and

significantly improve decision support mechanisms' precision and efficiency. Examining CUT managers' tasks provided insights into how BI tools support decision-making processes, contextualising their relevance in real-world scenarios.

The implications of the findings extend to other organizations, suggesting that understanding TTF can inform strategic decisions related to BI tool adoption and customization. Prioritising not only the technical capabilities but also the integration of BI tools into specific operational tasks is essential. Recommendations include the continuation of optimising efforts for the ITS online system's BI tool, including ongoing training programs, refining the tool based on technological advancements, and periodic assessments of task-technology fit. The assessment has limitations, including the need for future research on the long-term impact of BI tools and a deeper understanding of stakeholders' perspectives. Despite these limitations, the assessment underscores the importance of TTF in maximizing BI tool potential at CUT, enhancing decision-support mechanisms, and contributing to managerial process effectiveness. The study significantly enhances our understanding of BI fitness for decision-making within academic institutions, emphasizing the importance of TTF and challenging the notion that increased system usage directly correlates with improved BI fitness. The study's methodological approach, including advanced statistical techniques like SEM ensures the reliability and validity of its conclusions.

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LIST OF ANNEXTURES AND APPENDIXES

ANNEXTURE 1: RESEARCH COVER LETTER



Study towards An Assessment of the Fitness of ITS online system Tools in Supporting Decision Making Processes at South African University: the case of Central University of Technology, Free State (CUT)



RESEARCH INVITATION LETTER

Date 24 June 2020

Dear prospective participant,

You are invited to take part in a research project focusing on assessing the fitness of the Integrated Tertiary Software (ITS) online system used at the Central University of Technology, Free State. This study targets academic and support senior managers who utilise ITS as a Business Intelligence (BI) tool to support in their decision-making processes.

The survey aims to assess the actual usage and user satisfaction of ITS, which are influenced by task characteristics, technology characteristics, and task technology fit. The findings will contribute to existing knowledge in this area. Your participation will be treated with confidentiality and anonymity, as records identifying you as a participant will be safeguarded by the main researcher and the ethics of the CUT research committee.

Should you have any questions regarding this study, please feel free to contact the main researcher, Ms. V. Njokweni, at vnjokweni@cut.ac.za.

Thank you for your participation.

Sincerely,

Ms. V. Njokweni



Central University of Technology, Free State, South Africa

ANNEXTURE 2: CONSENT FORM



Study towards An Assessment of the Fitness of ITS online system Tools in Supporting Decision Making Processes at South African University: the case of Central University of Technology, Free State (CUT)

CONSENT FORM		
I, the undersigned, confirm that (please tick box as appropriate):		
[1]	I have read and understood the information about the research,	☐
[2]	I have been given the opportunity to ask questions about the research and my participation.	☐
[3]	I voluntarily agree to participate in the research.	☐
[4]	I understand I can withdraw at any time without giving reasons and that I will not be penalized for withdrawing	☐
[5]	The procedures regarding confidentiality have been clearly explained to me.	☐
[6]	If applicable, separate terms of consent for forms of data collection have been explained and provided to me.	☐
[7]	The use of the data in research, publications, sharing and archiving has been explained to me.	☐
[8]	I understand that other researchers will have access to this data only if they agree to preserve the confidentiality of the data and if they agree to the terms I have specified in this form.	☐
[9]	Please select only ONE of the following:	
	I would like my name used and understand what I have said or written as part of this research will be used in reports, publications, and other research outputs so that anything I have contributed to this project can be recognised.	☐
	I do not want my name used in this research.	☐
[10]	I agree to sign and date this informed consent, along with the Researcher.	☐
Name of Respondent: _____ Signature: _____ Date: _____ Name of Researcher: _____ Signature: _____ Date: _____ Please tick the box to indicate your agreement: [] I agree to the terms outlined in this consent form.		

ANNEXTURE 3:RESEARCH ETHICAL CLEARANCE



FACULTY OF ENGINEERING, BUILT ENVIRONMENT AND INFORMATION TECHNOLOGY RESEARCH AND INNOVATION COMMITTEE

RESEARCH ETHICS APPROVAL LETTER

Date: 25 April 2019

This is to confirm that:

Applicant's Name	Ms V Njokweni,
Supervisor Name for Student Project (where applicable)	Prof M Masinde
Level of Qualification for Student Project (where applicable)	Master in Information Technology (Central University of Technology)
Title of research project	An Assessment of Business Intelligence Tools' Fitness in supporting Decisions Making Processes in South Africa's Universities of Technology: Case of CUT

Ethical clearance has been provided by the Faculty Research and Innovation Committee on 25 April 2019 in view of the CUT Research Ethics and Integrity Framework, 2016 with reference number FEBIT 4/19 – 6.10/25-04-2019.

The following special conditions were set:

☒ None

☐ Specific conditions

We wish you success with your research project.



Dr JG van der Walt
(FRIC Chairperson)

ANNEXTURE 4:RESEARCH INSTRUMENT-SURVEYMONKEY ONLINE QUESTIONNAIRE:



Study towards An Assessment of the Fitness of ITS online system Tools in Supporting Decision Making Processes at South African University: the case of Central University of Technology, Free State (CUT)

PART A: BIOGRAPHICAL INFORMATION

Q1. What is your gender?		☐ Male ☐ Female ☐ Not specified (Other)
Q2. What is your age?		☐ 36 to 45 ☐ 46 and above ☐ 18 to 25 ☐ 26 to 35
Q3. Highest Academic Qualification		☐ Matric ☐ College certificate but not Diploma ☐ Diploma ☐ Degree ☐ Postgraduate
Q4. How would you describe your role or Job description?		
☐ Executive Academic Teaching Support (DVC ,Dean) ☐ Senior Academic Teaching Support (HOD ☐ Senior Support Staff (Faculty Officer, Assistant Registrar, Deputy Director)		☐ Executive Support Staff (DVC, Registrar, Director, Assistant Registrar) ☐ Academic Teaching Support (Lecturer ,Senior Lecturer, Departmental Manager, Coordinator) ☐ Support staff (Academic Admin, Admin Officer, Officer, Personal Assistance, Secretary)
Q5. Years of experience in the job		
☐ Less than 5 years ☐ 11 to 15 years ☐ 21 to 25 years		☐ 6 to 10 years ☐ 16 to 20 years ☐ 2 years and above

PART B: Fitness of ITS online system used for tasks at CUT.

6. Select ITS online subsystem you use for your tasks and specify how frequency you use it

☐ Student Selection System (Selection of applicants for prospective and senior students)	☐ ITS online financial management system	☐ ITS online Human resource management and Payroll	☐ ITS online Management information and Facilities Management
Student Selection Sub-System	Finance I Enabler Sub-System	Personnel Web Sub-System	Management information and Facilities Management Sub-System
Lecturer Web	Requisitions	Leave System	Access Control/Request for Information/Library system
☐ Timetable	☐ Create Requisition	☐ Leave Application	☐ View your ITS Access Profile
☐ Class List	☐ Maintain Requisition	☐ Leave Cancellation	☐ Request for Information
☐ Enter Paper Marks	☐ Approve Requisition	☐ Approved Leave Cancellation	☐ Approved Leave Cancellation
☐ Enter Exam Marks	☐ Expense Budgeting	☐ Leave Approval	☐ Search my items on Loan
☐ Enter Final Marks	☐ Salary Budgeting	☐ Personal History	☐ Search my Circulation History
☐ Assignment Information	☐ Budget Query	☐ History of Employees	☐ Search my Previous Searches
☐ Enter Exam Question Marks	☐ Cost Centre Query	☐ Leave Calendar	☐ Search my Fines
☐ Activity Class List		☐ Calendar of Employees	☐ Search Items on Hold
☐ Weight/Subminimum (PNAM)		☐ Balances of Employees	☐ Search my interests

☐ Cohorts		Personal Maintenance	☐ Suggest an Item
☐ Attendance Register		☐ Personnel Biographical	
☐ Assessment Marks		☐ Communication Detail	
☐ Process Student Appeals		☐ Address Detail	
		☐ Performance Evaluation	



Study towards An Assessment of the Fitness of ITS online system Tools in Supporting Decision Making Processes at South African University: the case of Central University of Technology, Free State (CUT)

7.	Rate the extent to which the ITS online system contributes to your tasks.				
	Strongly Agree	Agree	Neither Agree nor Disagree	Disagree	Strongly Disagree
ITS online system is easy to use.	☐	☐	☐	☐	☐
The system is user-friendly.	☐	☐	☐	☐	☐
It is always available.	☐	☐	☐	☐	☐
ITS online is a reliable system.	☐	☐	☐	☐	☐
System is useful and relevant to my tasks.	☐	☐	☐	☐	☐
System is secure.	☐	☐	☐	☐	☐
Is a stable system.	☐	☐	☐	☐	☐
It provides accurate information.	☐	☐	☐	☐	☐
It provides (useful) clear and understandable information.	☐	☐	☐	☐	☐
Provides information timely.	☐	☐	☐	☐	☐
It provides usable information that meets users' tasks.	☐	☐	☐	☐	☐
System is integrated with other systems.	☐	☐	☐	☐	☐

8.	Impact of using the ITS online system on individuals' work tasks.				
	Strongly Agree	Agree	Neither Agree nor Disagree	Disagree	Strongly Disagree
ITS online helps me to accomplish my tasks more quickly.	☐	☐	☐	☐	☐
Makes it easier to complete my tasks.	☐	☐	☐	☐	☐
It enhances academic support effectiveness.	☐	☐	☐	☐	☐
Assist to eliminate errors in my work tasks.	☐	☐	☐	☐	☐
Helps to acquire new skills and knowledge.	☐	☐	☐	☐	☐
It assists to come up with innovative ideas.	☐	☐	☐	☐	☐

9.	Indicate your satisfaction using ITS online system.				
	Strongly Agree	Agree	Neither Agree nor Disagree	Disagree	Strongly Disagree
I am satisfied, pleased, content with the system's efficiency.	☐	☐	☐	☐	☐

10.	Indicate individual decision-making satisfaction towards <u>organisation support</u>				
	Strongly Agree	Agree	Neither Agree nor	Disagree	Strongly Disagree
I am pleased with the quality (accurate correct, precise) decision I made using information provided by system.					

**Study towards An Assessment of the Fitness of ITS online system Tools in
Supporting Decision Making Processes at South African University: the case of
Central University of Technology, Free State (CUT)**

The decision process is efficient (saves time and is easier to perform)	☐	☐	☐	☐	☐
Indicate individual decision making satisfaction towards organisation support	☐	☐	☐	☐	☐
It helps me to involve my colleagues in making decisions	☐	☐	☐	☐	☐

		Extremely likely	Very likely	Moderate likely	Slightly likely	Not at all likely
11.	How likely are you to upgrade your subscription in the next 12 months?	☐	☐	☐	☐	☐

ANNEXTURE 5: PARTICIPANTS RESPONSES

Study towards An Assessment of the Fitness of ITS online system in Supporting Decision Making Processes at South African University: the case of Central University of Technology, Bloemfontein

#3

COMPLETE

Collector: An Assessment ...nline system (Web Link)
Started: Sunday, June 28, 2020 8:35:52 AM
Last Modified: Sunday, June 28, 2020 8:40:32 AM
Time Spent: 00:04:39
IP Address: 105.12.1.8

Page 2

Q1 **Male**

What is your gender?

Q2 **46 and above**

What is your age?

Q3 **Postgraduate**

Highest Academic Qualification

Q4 **Senior Academic Teaching Support (HOD)**

How would you describe your role?

Q5 **21 to 25 years**

Years of experience in the current Job

Page 3: PART B:ITS online system that are being used to perform user's task at CUT

Study towards An Assessment of the Fitness of ITS online system in Supporting Decision Making Processes at South African University: the case of Central University of Technology, Bloemfontein

Q8

Impact of ITS Online System usage on individual's work tasks

ITS online helps me to accomplish my tasks more quickly.	Agree
Makes it easier to complete my tasks	Agree
It enhances academic support effectiveness	Agree
Assist to eliminate errors in my work tasks	Neither Agree nor Disagree
Helps to acquire new skills and knowledge	Agree
It assists to come up with innovative ideas	Agree

Q9

Indicate your satisfaction on using ITS online system

I am satisfied, pleased, content with the system's efficiency.	Agree
--	-------

Q10

Indicate individual decision making satisfaction towards organisation support

I am pleased with the quality (accurate, correct, precise) decisions I made using information provided by the system	Agree
The decision process is efficient (saves time and is easier to perform)	Neither Agree nor Disagree
Indicate individual decision making satisfaction towards organisation support	Agree
It helps me to involve my colleagues in making decisions	Agree

Q11

Respondent skipped this question

How likely are you to upgrade your subscription in the next 12 months?

ANNEXTURE 6:LANGUAGE EDITING CERTIFICATE



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