Cape Peninsula
University of Technology

ARTIFICIAL INTELLIGENCE-ENABLED DECISION SUPPORT SYSTEM FOR SOUTH AFRICAN HIGHER EDUCATION INSTITUTIONS

by

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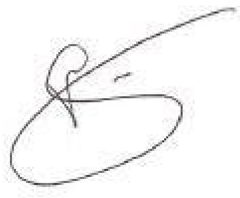
DECLARATION

I, Vusumzi Neville Funda, declare that the contents of this dissertation/thesis represent my own unaided work, and that the dissertation/thesis has not previously been submitted for academic examination towards any qualification. Furthermore, it represents my own opinions and not necessarily those of the Cape Peninsula University of Technology.



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ABSTRACT

This study aimed to develop a prototype artificial intelligence-enabled decision support system tailored for South African higher education institutions, recognising the growing significance of such systems in the dynamic landscape of universities. As universities evolve beyond traditional roles into data driven entities, decision-making has become increasingly complex, requiring real-time insights, connectivity and automation. However, the implementation of AI in higher education remains limited. Consequently, there is an actual need for AI-enabled decision support systems within university ICT departments to enhance operational efficiency and provide timely decision-making. This study sought to address this gap by creating an intelligent system that harnessed university data and adapted to changing circumstances, offering prompt, efficient and high-quality service. By relieving ICT support personnel from routine tasks and minimising downtime, this AI-enabled system aimed to enhance customer satisfaction. The research question for this study was how can an AI-enabled decision support system be developed for decision-making within the ICT department at the university?

The problem's relevance lies in the need for efficient decision-making processes in South African higher education institutions, as demonstrated by this study using the ICT department as unit of analysis. By leveraging the Design Science Research methodology, this study integrated Architectural design theory and Decision theory in developing the artefact. Ontological pragmatism and intersubjective epistemology were employed to address an existing real-world problem. The study initiated semi-structured interviews to identify challenges within the university's ICT department. Subsequently, the AIDSS prototype was developed. This prototype incorporated business automation, preventive asset maintenance, and predictive analytics functionalities to comprehensively address the identified issues. Business automation aimed to streamline operations and enhance efficiency by automating routine tasks. Preventive asset maintenance focused on proactively identifying and resolving potential IT infrastructure issues, reducing downtime. Predictive analytics leveraged data to provide insights for informed decision-making. The AIDSS prototype's development marked a crucial step towards improving operational efficiency and enabling data-driven decision-making within the ICT department.

Rigorous research evaluation methods, including Goal Question Metric and stakeholder feedback using a questionnaire were employed to assess the artefact's effectiveness, usability and impact. Through iteration, continuous improvements and refinements were made to the artefact, considering the unique context and needs of South African higher education institutions. The study contributes to the field by providing a novel and practical solution that enhances decision-making processes, empowers ICT personnel and advances the understanding of AI-enabled decision support systems in the higher education context. In addition, this study engaged in seminal and recent literature and debates on the subject of AI. Thus, the main theoretical contributions were in the generation of knowledge and theory towards the Information Systems discipline.

The study established that the artefact would enhance the skills and expertise of ICT personnel; it also provides information that helps users to make decisions effectively. It was also revealed that the system provided appropriate error messages and clear instructions of how to address the errors. In addition, the system successfully predicted and prevented impending ICT issues before they escalated. With these findings, the researcher acknowledges that the artefact contributed to the broader field of AI in higher education, offering practical insights that could guide future research and inform policy making in the context of information systems within academic institutions. The principal objective of this study was to develop an AI-enabled decision-support system; therefore, an artefact was produced at the end of the study.

Keywords: Artificial Intelligence, Decision Support Systems, Higher Education, Decision-making, Design Science Research

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DEDICATION

I dedicate this thesis to my mother Thenjiwe Thelma Funda.

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GLOSSARY

Acronyms	Definitions
AGI	Artificial General Intelligence
AI	Artificial Intelligence
AIDSS	Artificial Intelligence-enabled Decision Support System
AIOPS	Artificial Intelligence for Information Technology Operations
ANI	Artificial Narrow Intelligence
ANNs	Artificial neural networks
ASI	Artificial Super Intelligence
AUC	Area Under Curve
BPA	Business Process Automation
BPM	Business Process Manager
CPU	Central Processing Unit
DMS	Decision Making System
DMZ	Demilitarized Zone
DSR	Design Science Research
DSRM	Design Science Research Methodology
DSS	Decision Support System
EIS	Executive Information System
ES	Expert Systems
ET	Educational Technology
FPR	False Positive Rate
GPT	Generative Pretrained Transformer
GQM	Goal Question Metric
HCI	Human-computer interface
HEDA	Higher Education Data Analysis

Acronyms	Definitions
HEI	Higher Education Institutions
IBM	International Business Machines Corporation
ICT	Information and Communication Technology
IS	Information Systems
ISA	Information Systems Architecture
IT	Information Technology
ITIL	Information Technology Infrastructure Library
ITSM	information technology service management
KPIs	Key Performance Indicators
LAN	Local Area Network
ML	Machine Learning
MMI	Man-machine interface
NLP	Natural Language Processing
OECD	Organisation for Economic Co-operation and Development
OGC	Open Geospatial Consortium
PC	Personal Computer
POPIA	Protection of Personal Information Act
ROC	Receiver Operating Curve
SLA	Service-Level Agreement
SVC	Support Vector Classifier
TPR	True Positive Rate
UFH	University of Fort Hare
UNDP	United Nations Development Programme
UNESCO	United Nations Educational, Scientific and Cultural Organisation
YOLO	You Only look Once

CHAPTER 1: INTRODUCTION

1.1 Introduction

Rapid technological advancements are compelling organisations to make decisions in the adoption of technologies which, in some instances, are not aligned with the organisation's strategic objectives (Mora, Marx-Gómez, Wang & Gelman, 2014). The ramifications of poor decision-making are wasted resources on technologies that do not support the organisation's vision. Chi, Denton and Gursoy (2020) state that the emergence of Artificial Intelligence (AI) technologies has ushered in an era of developing intelligent computers that mimic human intelligence and functions such as learning and problem-solving. These human cognitive problem-solving functions demand a good degree of deductive reasoning, logic and expectations. Thus, with AI computers employ logic and mathematics to mimic reasoning enabling them to acquire knowledge from data and make informed choices (Smith & Neupane, 2018). Organisations exposed to Big Data use AI to provide advanced data analytics of critical information timeously for real-time data-driven decision-making (Chi, Denton & Gursoy, 2020). Philips-Wren (2012) states that decision-making is an inherently human activity that can impact a company's operations. Therefore, advances in Artificial Intelligence are improving the quality of decisions to augment human capabilities. Intelligent decision support systems (IDSS) or AI-integrated decision support systems are gaining popularity in cybersecurity, marketing, finance, healthcare and commerce. AI is applied to reason, learn, analyse and remember human behaviour (Philips-Wren, 2012). Computers can imitate people's reasoning skills using neural networks. Neural networks are forms of programs designed in the same way as the human brain works. Schwab and Zech (2019) posit that these algorithms enable computers to engage in deep learning through AI. Thus, with Artificial Neural Networks, decision-makers in Higher Education Institutions (HEIs) can evaluate and select alternative decisions, especially in complex problems involving uncertainty or large volumes of data with universities.

HEIs, as a repository of knowledge and information, deal with Big Data which should be mined and analysed to provide insights into university operations and administration. Given the large volumes of data and the importance of making timeous and informed decisions, universities need systems that extract data and analyse and present this data into dashboards for easier interpretation (Chi *et al.*, 2020). In IT operations, Big Data refers to the vast volume, variety, and velocity of data generated during the functioning of information technology systems. It encompasses the collection, processing, and analysis of extensive datasets, including event logs, alerts, metrics, and other data sources (Shilpa & Kaur, 2013; Rajasekar, Dhanamani & Sandhya,2015; Borodo, Shamsuddin & Hasan, 2016). Big Data in IT operations involves the use of advanced analytics and technologies to extract valuable insights, identify patterns, and make informed decisions (Leung, 2019). The goal is to manage and derive meaningful information from the sheer scale and diversity of data generated by IT systems, contributing to improved efficiency, enhanced decision-making, and optimisation of IT infrastructure (El-Gendy & Elragal, 2014). In the context of administrative work in Higher Education Institutions, Big Data refers to the vast and diverse volume of data generated across various departments and functions. It encompasses information from student records, enrolment data, financial transactions, faculty activities, research outputs, and more. Though university systems support the overall university operations, the primary challenge is that these university systems operate as stand-alone and silo systems (Ruiz, Moreno, Dorronsoro & Rodriguez. 2018). Silo approaches stifle information and knowledge sharing and make decision-making complex and challenging. For example, top-level management may need to make decisions that impact employees and students, but with fragmented information residing in distinct locations, decision-making may not happen as planned (Ruiz et al., 2018). Karaarslan and Aydin (2021) define decision-making as taking the best action among alternatives to solve a particular problem. Decision makers confronted with a large amount of data and information are faced with the dilemma of making the right and effective decisions. In the university environment, they may use traditional strategies and tools that can be utilised to transform this data into insights that aid managers in solving problems. Thus, prolonging the decision-making process, which ultimately affects students and employees. Given the prevalence of semi-structured decisions, analytical models or technology aiding can assist human judgment to present results and help the decision-maker interpret outcomes from the decision model (Philips-Wren, 2012). Making decisions requires the utilisation of software tools that aid in the decision-making process. Susnea (2013) asserts that these tools are essential for optimising university performance and minimising any effects caused by errors or faults.

Public-funded universities in South Africa have recently been confronted with a myriad of challenges. These encompass the onset of the Coronavirus Disease 2019 (COVID-19), changing the higher education landscape, employees' and students' expectations, and the need for management to make informed decisions (Abumandour, 2020). These challenges demanded managerial problem-solving to respond to market needs and expectations. For instance, South African universities were confronted with decisions about purchasing Internet-enabled devices and resources for employees and students, transitioning to online learning management systems, examination proctoring, and change of the assessments. These decisions are what Berawi (2020) regards as incisive thinking to ensure that informed decisions are made for the university. Given the silo approach of information and knowledge sharing inherent in universities, leadership did not have access to a basket of information, which could expedite the decision-making process (Abumandour, 2020). Academics, administrators, management, and faculties keep information that is not readily shared. For instance, the COVID 19 crisis has posed challenges forcing decision makers and policymakers in universities to make choices given limited resources and uncertainties. In circumstances there arises a necessity for making decisions based on prioritisation (Berawi, 2020) .

Compounding the silo approaches inherent at universities, Chetty and Pather (2015) state that policies, culture, big data and a lack of digital leadership negatively affect decision-making. Faculties, departments and administrative units generate and preserve Big Data; thus, problems are associated with making decisions on widely distributed data. AI tools and techniques are often the method of choice for solving complex problems and combining AI and decision support approaches yields IDSS (Berawi, 2020). For instance, when we utilise Artificial Neural Networks we gain a tool for examining amounts of data and acquiring knowledge from that data. This allows us to identify patterns and uncover linear connections. This is a base for implementing modern technology like AI, generally acknowledged for its ability to improve and actively optimise Information Communication Technology (ICT) in real-time.

1.2 Research Problem

Decision-making is a complex process within the university environment (Susnea, 2013) which may entail operational resource allocation, student registration, enrolment, etcetera. The processes involved in decision-making require a timeous response and informed decisions to mitigate inconveniences on management, students and employees. The ICT department provides valuable tools and technologies for obtaining and analysing data. Given this complex nature, the ICT department often must make informed and timeous decisions based on the large amounts of data generated from different faculties and departments (Manda & Dhaou, 2019). In addition, the available Artificial Intelligence tools available on the market may not be well known by the HEIs. Compounding this problem is the silo approach that is widely adopted by HEIs. The selected HEI has a variety of information systems, operates in disconnected silos and generates large amounts of data which is complex to process using traditional approaches. The current operational decision-making processes within the ICT department of the case university lack synchronisation and operate in isolated silos. There is a noticeable absence of coordination among units; each functions independently, resulting in disjointed decision-making. Decisions made by the network unit may not align with those of the infrastructure unit, and the servicedesk operates without coherence with the enterprise resource planning unit, BPA, teaching and learning facilities, and IT operations. This lack of cohesion leads to scattered and uncoordinated decision-making processes across various facets of the ICT department.

The decision-making process has become more complicated due to the impact of the COVID 19 in 2020, where different faculties and departments produced diverse ideas, strategies and suggestions on responding to operational challenges despite having data management tools and techniques (Widianto & Subriadi, 2022). Management and employees struggle to make informed and timeous decisions using traditional approaches, but AI tools could significantly help if they were adopted and utilised in the HEI. In addition, a dearth of knowledge and information seems to have contributed to the lack of adoption of AI tools and technologies available. Universities must adopt decision support systems that suit the institutions' infrastructure and plan, as this can impact the efficacy of DSS. Laudon and Laudon (2004) state that the adoption of AI tools into the decision-making process can assist organisations in dealing with generated Big Data. Therefore, this study will develop an AI-enabled decision support system to support operational decision-making within the ICT department at a selected HEI in South Africa and other universities that could be facing similar challenges. From a theoretical perspective, studies on AI have been gaining momentum, but there is a paucity of studies that specifically focus on the HEI landscape in South Africa, region and continent. This huge literature gap could have been overlooked by researchers because the primary focus on AI advancements have been on commerce, industry and technology firms, alienating institutions of higher learning. Thus, the focal point of this study is to engage literature and contribute to AI debates and generate new knowledge that would be significant to the Information Systems discipline.

1.3 Research Questions and Objectives

This study aimed to develop an AI-enabled decision support system for South African Higher Education Institutions. To achieve this goal, one main research question (MRQ) complemented by four secondary research questions (SRQ1-SRQ4) guided the study. The four secondary research questions mapped to four research objectives (RO1 – RO4) establishing foci for the study (Table 1.1 below).

Table 1.1 Research Questions and Research Objectives

Research Questions	Research Objectives
MRQ: How can an AI-enabled decision support system be developed for decision-making within the ICT department at the university?	
SRQ1: What are the various decision-making elements that affect decision-making within the ICT department at the university?	**RO1:** To determine how various decision-making elements affect decision-making within the ICT department at the university.
SRQ2: How is operational decision-making performed within the ICT department at the university?	**RO2:** To determine how operational decision-making occurs within the ICT department at the university.
SRQ3: What challenges are decision-makers facing when making operational decisions within the ICT department at the university?	**RO3:** To assess challenges faced by decision-makers when making operational decisions within the ICT department at the university.
SRQ4: How can an AI-enabled decision support system be developed for decision-making within the ICT department at the university?	**RO4:** To develop an AI-enabled decision support system to support operational decision-making within the ICT department at the university.

1.4 Research Context of the study

The selected case university, established in 1916, is situated in the Eastern Cape region of South Africa. This university holds significance for education in South Africa as it was among the higher education institutions for black South Africans. Initially its primary purpose was to train teachers. As time went on it expanded its offerings. Became a renowned centre for education and intellectual discussions, among black students. Eventually the university underwent a restructuring process that led to the establishment of three campuses. The main campus continued to offer a range of academic programs complemented by two additional campuses. These campuses aimed to provide more accessibility and educational opportunities for students in different regions.

Currently, the University has six faculties, namely:

- Faculty of Education.
- Faculty of Law.
- Faculty of Management and Commerce.
- Faculty of Science and Agriculture.
- Faculty of Social Sciences and Humanities.
- Faculty of Health Sciences.

It continues to be a reputable institution, renowned for its dedication, to upholding standards and promoting social justice. The institution provides an array of graduate programs spanning across multiple fields of study, contributing to the development of South Africa's educational landscape. The provided graphical representation in Figure 1.1 below depicts the organisational hierarchy of the selected case university.

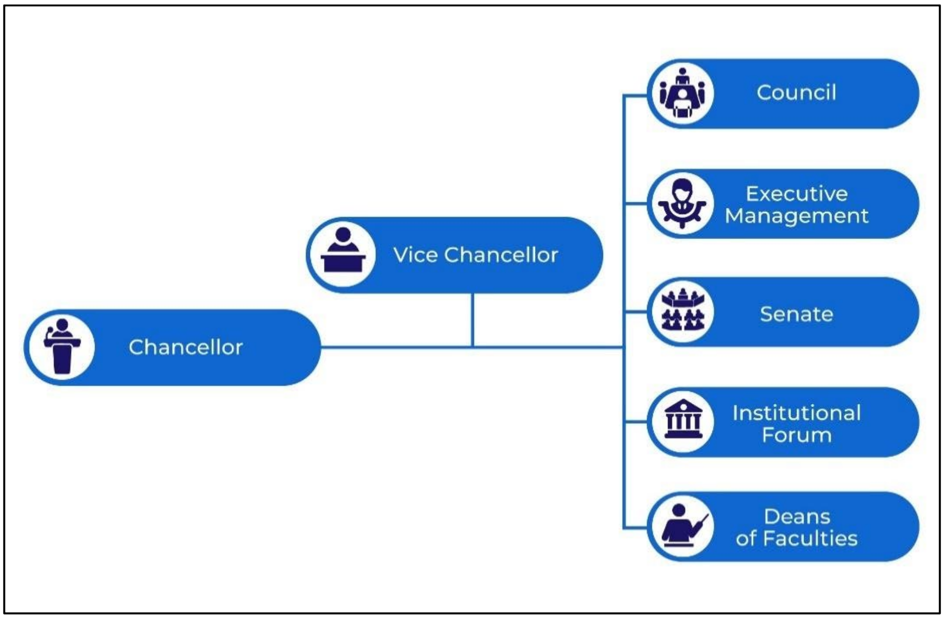


Figure 1.1 Leadership structure

The university boasts contemporary amenities and remarkable infrastructure for teaching and learning. Its student body highlights diversity in terms of race, gender, and nationalities, as evidenced by the Higher Education Data Analysis (HEDA).

One of the institution’s core values is service culture, which ought to encourage its ICT department to adopt a customer-centric approach, establish efficient service desk functions, adhere to ITSM principles, and promote collaboration and communication amongst stakeholders. This ties with the aim of this research of developing an AIDSS for higher education institutions. By integrating service culture into IT operations, organisations can enhance the delivery of IT services and ensure a positive user experience.

1.5 Data of Case Institution

Table 1.2 provides a comprehensive overview of the selected university's real-time data spanning across the academic years 2019, 2020, and 2021.

Table 1.2 Peer Data Report (powerHEDA, 2023)

Items	2019	2020	2021
Student Headcount Enrolments	16982	15880	15897
Staff full time equivalent	1500	1393	1427
Staff v Student ratio	34.90	34.66	35.18
Research Output	682	659	555
Graduate report	3014	3632	3425

These data points offer valuable insights into various aspects of the university's functioning, including student enrolment, staff numbers, research activities, and graduate reports. In 2019, the university had a total student headcount enrolment of 16,982, which slightly decreased to 15,880 in 2020, and then remained relatively stable at 15,897 in 2021. Concurrently, the full-time equivalent staff members numbered 1,500 in 2019, reduced to 1,393 in 2020, and showed a modest increase to 1,427 in 2021. These figures are indicative of the institution's size and workforce across the three years. The staff-to-student ratio is another critical metric displayed in the table. In 2019, this ratio was 34.90, indicating that there were approximately 34.90 students for every staff member. This ratio remained quite consistent over the years, with a minor decrease in 2020 (34.66) and a slight increase in 2021 (35.18). This metric provides insights into the level of personalized attention and support students can expect from the staff. Furthermore, the table illustrates the university's research output. In 2019, there were 682 research outputs, which decreased to 659 in 2020, and further declined to 555 in 2021. These figures shed light on the institution's research activities and productivity over the years, highlighting potential areas of growth or focus.

Lastly, the table depicts graduate report figures. The number of graduate reports was 3,014 in 2019, which saw a substantial increase to 3,632 in 2020, followed by a decrease to 3,425 in 2021. These figures reflect the number of students who successfully completed their academic programs during the respective years.

In summary, Table 1.1 serves as a valuable resource for understanding the selected university's key performance indicators and trends over the specified academic years. It offers a comprehensive snapshot of student enrolment, staff resources, staff-to-student ratios, research output, and graduate reports, providing a basis for further analysis and decision-making.

The data reflected in Figure 1.2 below includes information on the number of students enrolled in undergraduate programs, postgraduate programs, diploma courses, certificate programs, and other academic qualifications offered by the selected university. It captures the total count of students within each qualification category, providing a snapshot of the overall distribution and composition of the student body.

	Calendar year					
Qualification type Institution Active	2016	2017	2018	2019	2020	2021
	Headcounts	Headcounts	Headcounts	Headcounts	Headcounts	Headcounts
Advanced Certificate	96	109	161	106	79	39
Advanced Diploma	-	79	76	63	52	40
Bachelor Honours Degree	590	703	814	941	830	859
Bachelor's Degree (360)	4 691	5 168	6 237	6 730	6 665	6 535
Bachelor's Degree (480 - NQF level 7)	-	-	-	-	303	1 694
Bachelor's Degree (480)	2 190	2 471	3 574	4 183	5 223	4 392
Diploma	133	161	175	234	199	150
Diploma (360)	-	-	49	48	65	89
Doctoral Degree	688	778	791	640	486	451
General Academic First Bachelor's Degree	560	619	-	-	-	-
Higher Certificate	79	115	106	82	43	5
Honours Degree	191	233	415	126	-	-
Master's Degree	1 105	1 252	1 379	1 445	977	888
Masters Degree	148	297	339	3	1	-
Occasional student	21	32	19	32	19	49
Post Graduate Certificate in Education	-	-	-	109	117	167
Post Graduate Diploma	203	266	273	224	253	278
Post-graduate Bachelor's Degree	49	45	37	-	-	-
Postgraduate Diploma	28	-	34	34	-	-
Post-graduate Diploma or Certificate	274	203	142	51	-	-
Professional First Bachelor's Degree (3 years)	93	68	45	18	9	2
Professional First Bachelor's Degree (4 years or more)	2 657	2 791	2 229	1 913	559	259
Undergraduate Diploma or Certificate (3 yrs)	35	36	1	-	-	-
Total	13 831	15 426	16 896	16 982	15 880	15 897

Figure 1.2 Student Headcount by Qualification (powerHEDA, 2023)

1.6 IT Operations in the Case Institution

In the case institution being studied and in today's digital age, IT operations have become an integral part of daily activities, supporting the delivery of services and enhancing the overall student and staff experience. The ICT department at the case university is responsible for managing complex IT infrastructures, maintaining important levels of service availability, and ensuring that the technology aligns with the institution's goals and objectives. Specifically, the ICT department holds the responsibility for the day-to-day supervision and oversight of all ICT-related components across the three campuses of the case university. This operation covers a spectrum of communication tools and applications such as computer and network equipment, software, telephone systems well as related services and applications, like video conferencing and online education. shown on Figure 1.3 below.

Figure 1.3 ICT services

The role that IT operations play within the HEI allows us to uncover the challenges and opportunities that the ICT department encounters in this scenario. Moreover, it sheds light on their efforts to provide effective IT services that align with the institution's mission and objectives. The following are some of the functions rendered by the ICT department at the case university to staff, students and visitors:

1.6.1 ICT Support

The Service Desk serves as a centralised hub, offering comprehensive computing and networking services for users at the case university. It serves as a convenient and accessible point of contact for all levels of support. ICT users have the option to visit any of the three physical "walk-in" Service Desks. The service desk is a customer support unit responsible for providing telephone-based ICT assistance. This includes managed PCs, departmental customer service for faculty and students, and more (Keengne & Georgina, 2017). In addition, they offer lecturer and student training opportunities (Dube & Gumbo, 2017). At the case university, IT Incidents and problems involve logged calls to the service desk or Cherwell service management software accessible via the web, which is a helpdesk ticketing system, that also serves to track each call as depicted below Figure 1.4 below. Until recently, only email systems facilitated the logging of ICT queries, service requests, and faults.

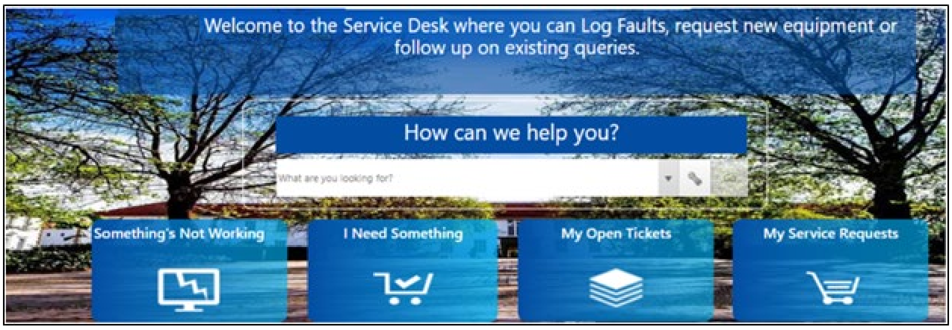


Figure 1.4 Call logging system (author, 2023)

To use the Cherwell service management software staff and students must authenticate with their email address and password. Once logged in, they can log an incident if something is faulty or if they require a service/device. In both instances a screen displays requests for user details. The user provides relevant information and submits details to send the request. To follow up on outstanding incidents such as tracking submitted but unresolved requests, the user clicks on “My Open Tickets”. Users select “My Service Requests” to list all service requests they logged into the system and to review unresolved and open requests. The primary objective of the SD is to address and resolve 70% of all inquiries either through telephone assistance or by utilising Lync remote access software. In cases where remote resolution is not feasible, a technician receives routed calls delivered to the user's location to provide aid.

1.6.2 Network and data management

The network unit provides support to the entire organisation and is responsible for the administration of systems and networks, the deployment of desktop hardware and software, and classroom technology (Keegan, 2003). They are responsible for improving the whole environment of information and communications technology, which includes bolstering information security. Significantly emphasised information security includes firewalls, antivirus software, security regulations, and technology meant to make networks less susceptible to attack (Trucano *et al.*, 2007). The case university's Enterprise Systems and Network unit is responsible for management and maintenance of the university's computer network infrastructure, ensuring reliable and secure connectivity across Alice, Bisho and East London campuses. This includes managing wired and wireless networks, network security, and troubleshooting network-related issues with support from 3rd party service providers. The Figure 1.5 below depicts a structure of the local area network (LAN) at the case university, including the connectivity between campuses and relevant details.

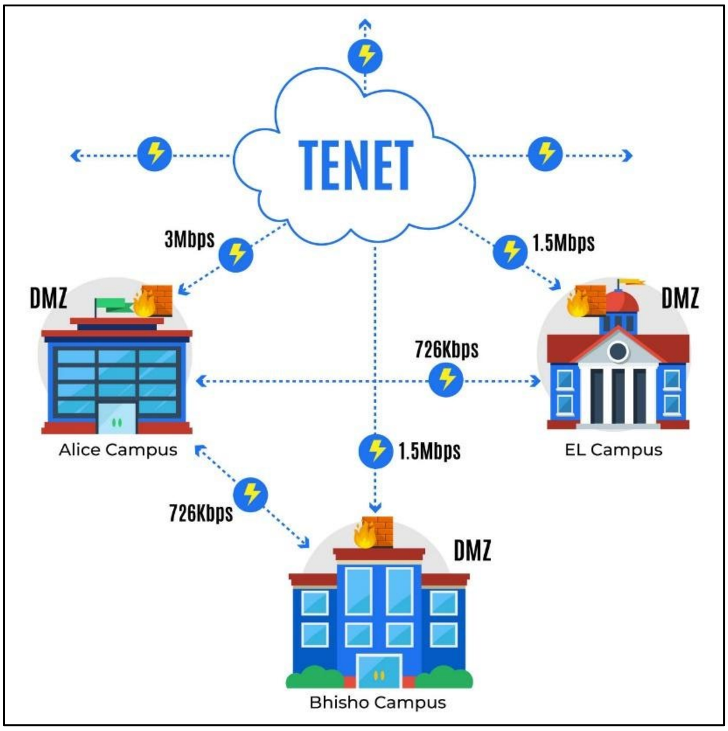


Figure 1.5 Network Topology (adapted from Mudziwepas & Scott, 2014)

The case university utilises a Hybrid Star Topology to connect its three campuses. Integrated Services Digital Network (ISDN) lines are employed as the means of linking these campuses together. Each campus includes a Demilitarized Zone (DMZ) firewall, ensuring that external intruders and hackers are unable to access the university's intranet from outside the campuses. By serving as a security barrier, the DMZ firewall requires all incoming traffic from the outside world to pass through it to access the LAN within each campus. Consequently, the LAN functions as a private network, safeguarding the university's internal communications and data.

The network unit maintains and upgrades all servers and services listed below:

- Authentication.
- Directory Services.
- Dynamic Host Configuration Protocol.
- Distributed Network Service (DNS).
- Electronic Mail.
- Network File System.
- Web Hosting.
- Simple Network Management Protocol.
- Installation and Maintenance of all Wireless Access Points on all three campuses.
- Network Design and Development.
- Storage Area Network.
- VMWare.

1.6.3 Electronic File Storage

The electronic file storage service offers secure storage space for electronic data to staff, students, and groups. It encompasses several components, including the provision of individual and group file storage with allocated quotas. Users can request the creation of group file storage and sharing, ensuring collaborative work and efficient data management. Additionally, the service includes a reliable process for archiving the university's intellectual property, ensuring the safe preservation of valuable resources and knowledge. The implementation of server-based virus scanning aims to maintain a secure environment, protecting stored data from potential threats. Furthermore, the service encompasses capacity and usage monitoring to effectively manage storage resources. This monitoring system enables the identification of trends, optimisation of storage utilisation, and proactive measures to address potential capacity limitations. This service provides staff, students, and groups with a secure and organised solution for storing electronic data. Through features such as individual and group file storage, archiving of intellectual property, virus scanning, and capacity monitoring, the service supports data management needs while maintaining a secure and efficient storage environment.

1.6.4 Teaching facilities and Student laboratories

This ICT service encompasses the maintenance and upgrade of all technical equipment used in teaching facilities and laboratories at the university. Its primary goal is to ensure a standard operating environment that enables a standard realisation of educational processes, online and offline. Maintenance activities play a vital role in this service, as skilled technicians regularly inspect and service the technical equipment deployed across university's teaching facilities and laboratories. These activities may include maintenance of computers, projectors, audio-visual equipment, scientific instruments, and other specialised devices. By conducting routine maintenance, the identification and addressing of any potential issues or malfunctions occurs promptly, ensuring that the equipment remains in optimal working condition. The teaching and laboratory service incorporates regular upgrades of technical equipment to keep pace with emerging technologies and industry standards. This includes replacing outdated or obsolete devices with modern, more efficient counterparts that enhance the teaching and learning environment. Upgrades may involve hardware improvements, software updates, or the installation of advanced features to support academic programs effectively. This ensures the establishment and maintenance of a standard operating environment across all teaching facilities and laboratories. This includes the standardisation of hardware configurations, software installations, and network connectivity. By implementing a consistent operating environment, case university can streamline technical support, facilitate collaboration among faculty and students, and simplify the usage of teaching resources. This service plays a crucial role in supporting teaching and learning initiatives by providing comprehensive maintenance, upgrades, and standardisation of technical equipment in teaching facilities and laboratories. Through these efforts, the case university can create an optimal learning environment that is conducive to effective teaching, research, and innovation.

1.6.5 Enterprise resource planning

The ICT department's Enterprise resource planning unit is responsible for ensuring that the institution's computing and networking infrastructure meets the needs of its academics, students, and researchers. They utilise their skills to execute strategic planning and project management for the university's ongoing projects. Hall and Hord (2006) point out that the group demonstrates its responsiveness to the HEI by offering assistance and direction for projects involving information and communication technologies, as well as by facilitating strategic project communication. In recent years, the role of IT operations within the HEI has become increasingly complex and critical, with the rapid pace of technological advancement and the growing expectations of stakeholders, including students, faculty, and staff. The ICT department must not only manage traditional IT infrastructure, but also adapt to innovative technologies, such as cloud computing, artificial intelligence, and big data analytics. Additionally, the increased reliance on digital platforms for teaching, learning, and administrative tasks has led to a greater need for ICT to maintain prominent levels of service availability, security and performance. One of the key challenges facing IT operations within the HEI is the need to balance competing priorities and limited resources. ICT must not only ensure the smooth functioning of existing IT infrastructure and services but also work on innovation and digital transformation initiatives that support the institution such as data driven decision-making (Teng *et al*., 2023).

The enterprise application services offered by the Enterprise resource planning unit provides staff and students with access to various portals within the IT infrastructure. These portals serve as essential tools for managing and administering financial, academic, and personnel data specific to the case university. Within the financial domain, staff and students can utilise the dedicated portals to efficiently handle financial tasks such as budgeting, expense tracking, financial reporting, and invoice management that are specific to the university's financial processes and requirements. In terms of academic data management, staff and students have access to portals tailored to the university's academic operations. These portals enable seamless management of academic records, curriculum development, course registration, grades, and assessment data. They provide a comprehensive platform to handle academic information specific to case university’s programs and courses.

For personnel data management, ICT offers portals that cater to the needs of staff members. These portals function as platforms for managing employee records, providing self-service options for employees, managing leave requests and conducting performance evaluations. Designs aim to meet the needs of personnel and ensure streamlined administrative processes. By providing access to these portals, ICT service enables staff and students to efficiently manage and administer critical financial, academic and personnel data within the university's context. The availability of these specialised portals contributes to the effective functioning of administrative processes at the case university, supporting the institution in achieving its goals and objectives.

1.7 Preliminary Literature Review

Conducting a literature review is critical for improved comprehension and knowledge of the subject at hand. This section focuses on what others have said and how they have arrived at their findings in studies closely related to AI and Decision Support Systems (DSS). Reviewing literature helps to understand key issues that underpin the present study, including delegating decision support to AI in HEIs, leading to the generation of new knowledge.

1.7.1 Artificial Intelligence

Stone *et al.* (2016) discovered that there is no accurate and commonly agreed definition of AI, despite its importance in research and practice. They describe AI as "a science and a collection of computer technologies that are inspired by—but often work somewhat differently from—the ways individuals detect, learn, reason, and take action". Russell and Norvig (2003) deduce four significant groups of AI definitions, including: "thinking humanely," "acting humanly," "thinking logically," and "acting rationally". Furthermore, current research divides between "strong AI," which is concerned with the development of artificial (i.e., human-like) intelligence, and "weak AI," which is concerned with AI-enabled systems that perform specific jobs (Kurzweil 2005; Stone *et al.*, 2016). This study focuses on operational decision-making in HEIs ICT department, regardless of whether they occur in a "human-like" fashion, according to Stone *et al.* (2016).

The primary distinction between AI and traditional software (e.g., decision support systems) is AI's capacity to learn from copious amounts of data in various forms and periods and derive conclusions from such data (Zuboff, 2023). The processing of data does not require pre-coding. Instead, it might evolve over time when the AI examines the data it receives as input through a machine learning process (Kellogg *et al.*, 2020). AI powered software can create its understanding of a decision-making challenge and offer its judgments on the optimal results for a stated aim using this learning mechanism (Dietvorst *et al.*, 2015).

AI in HEIs offers a wide range of applications leveraging advanced technologies and Big Data. As such, Calegari *et al.*, (2020) state that deep learning and neural networks have been boosted to exploit Big Data for forecasting and making autonomous decisions. Machine learning is commonly used in intelligent systems. Another feature of AI is natural language processing (NLP), which may be used to extract information from various scientific databases. Information demand can be described in natural language throughout the information retrieval process, making searching easier and more successful (Chilunjika et., 2022).

1.7.2 Intelligent Systems

A subset of Artificial Intelligence, namely Intelligent Systems (ISs), is described "as any formal or informal system" capable of obtaining and processing data, interpreting the data using artificial intelligence and business intelligence technologies, and providing reasoned judgements to decision-makers as a foundation for action (Sharda *et al.*, 2018). Intelligent systems can make decisions based on input, learning from past interactions, and adapting to new situations (Paulovich *et al.*, 2018). Such technologically advanced devices can operate under uncertain conditions while simultaneously possessing features such as adaptability, self-optimisation, self-diagnosis, and self-maintenance (Wang *et al.*, 2019; Manhiça *et al.*, 2022). The study of intelligent systems also explores how these systems interact with humans in physical environments that are always changing and dynamic. In their early stages of development, early robots did not possess the autonomy to make decisions. They assumed that the world was predictable, and they would carry out actions over and again when faced with similar circumstances. Breakthroughs in intelligent systems are radically altering our society and will change our future in ways never seen before (Schwab & Zech, 2019; Xing & Marwala, 2017). Intelligent systems are used in HEIs in several ways. These include admissions decisions, course scheduling, implementing systems to identify and support students who may be at risk, utilising tutoring systems and evaluating students' individual strengths and weaknesses. Other uses include fostering collaboration among learners, assessing and evaluating student performance, providing automated grading and feedback, gauging student comprehension and engagement ensuring academic honesty, evaluating teaching methods customising course content to suit individual learners needs, recommending personalised learning resources, assisting teachers in instructional design and planning and utilising academic data to monitor and guide students throughout their learning journey (Zawacki-Richer et al., 2019; Manhiça *et al*., 2022).

1.7.3 Expert Systems

Wijewickrema (2023) defines expert systems (ES) as systems that simulate human activities. ES caption human activities, so they can automate them. However, their limitation is that human activities are too many and change rapidly. Rhines (1985) states that given their limitations, ES in HEIs is being replaced by AI and Machine Learning (ML) systems which can learn and act without being told what to do every time. The argument is that ML and AI can simulate some aspects of human intelligence. Integrating expert systems into education institutions (HEIs) seeks to encompass the amount of knowledge acquired by individuals who have achieved expertise in particular fields. This accumulated knowledge is then employed to navigate scenarios replicating the problem-solving methods employed by experts. ML and AI are altering how decisions are made, and firms compute large amounts of data. ES comprises two essential components: a knowledge repository and an extrapolation engine for making quick decisions. Bavakutty *et al.* (2006) discovered that ISs use problem-solving skills in various fields, including medical, commerce, "computer science, law, defence, education, mathematics, engineering and geology".

1.7.4 Conceptualisation of Intelligent Decision Support Systems

The operational, financial, student enrolments, cancellations, deferrals, data generated from student and management information systems can be challenging for university staff and administrators to locate the valuable information needed for making informed decisions, in higher education (Susnea, 2011; 2013). In addition, different departments and faculties generate diverse but complex datasets about their faculties and departments. These datasets are not shared across departments and teams within the university, resulting in a silo approach to data, information and knowledge-sharing environment. Hence, the creation of a comprehensive AI system designed to aid decision-makers in promptly accessing administrative and operational data stands as a crucial stride towards the effective implementation of novel educational tools, policies, and technologies. This initiative empowers decision-makers to make well-informed choices in a timely manner (Susnea, 2013). This data pertains to various aspects of the university's organisational framework, including its structure, relationships, workflow patterns, supervisor assignments, as well as communication protocols between the system and its beneficiaries. Given the difficulties of dynamic decision-making, humans may perceive benefits in outsourcing decision-making or parts of the process to artificial intelligence.

1.7.5 Decision Support Systems (DSS)

This study aims to enhance the process of operational decision-making in the ICT department at the university by designing an AI-enabled DSS. Al Shobaki (2022) states that the concept of Decision Support Systems (DSS) gained prominence as executive management began harnessing information systems for the analysis of organisational data. This analytical process led to the generation of executive information, which in turn bolstered the decision-making process. With rapid technological advancements, so was the realization that organisations processed Big Data which complicated the extraction of information strategic imperatives (van Bon *et al.*, 2010). Table 1.3 below uncovers the shape and form of decision support systems.

Table 1.3 Decision support classification (adapted from Holsapple, 2008)

DSS Type	DSS Description
Data-driven DSS	Highlighting the importance of having access to and being able to access company data as well as occasionally external data, these systems can be categorised based on their level of sophistication. Initially they may consist of file systems along with tools, for querying and retrieving information. As they progress, they can evolve into data warehouses. Eventually they can utilise Online Analytical Processing (OLAP) or data mining tools for analysis purposes.
Communication Driven DSS	Leverage the power of network and communication technologies to enhance collaboration and enable communication.
Group DSS	Interactive computer-based systems enable a group of decision makers to collaborate and solve problems collectively.
Document Driven DSS	Combine storage and processing technologies to achieve document retrieval and analysis. They may consist of numerical data, written text as multimedia content.
Model Driven DSS	Highlight the importance of being able to utilise and modify a model such as financial, optimisation and/or simulation models. These models make use of data and parameters. Typically, do not require an amount of data.
Knowledge-driven DSS	Interactive systems designed to have problem solving abilities which include possessing knowledge about a domain, understanding the issues that arise within that domain and having the capability to effectively solve these problems.
Web Based DSS	Computerised systems provide managers and analysts with decision support information and tools. These systems are accessible through a "client" web browser.

As discussed by Holsapple (2008), these categories of DSS offer a spectrum of tools and functionalities to aid decision-makers in various aspects of their work.

DSS aims to offer the necessary information to help human decision-makers overcome the limitations and constraints they confront. Some South African universities could rely on legacy systems with pros and cons. The pros are their reliability and dependability as they have been used for decades. The downside for some systems is that they are not scalable or compatible with the latest enterprise resource planning systems and other advanced technologies such as ML, AI or robotics (ITG Institute, 2008). Universities rely on past data stored in their archives for decision-making, but this data is resident in different systems operating in silos. Some good examples of reports produced from historical data are descriptive analytics—for example, information about past performances. The preceding DSS report is key to this study because it is where different systems are pooled together (one database). Management uses AI and ML to mine data, analyse, interpret and make appropriate decisions. This entails decision support systems that help predict the future, a complex process not available in conventional DSS. Knowing what happened in the past is of limited use; therefore, Cutting-edge technologies have emerged, offering the capacity to forecast forthcoming trends and shifts that will exert an influence on universities or organisations, as highlighted by Schwab and Zech (2019). This is referred to as predictive analytics and constitutes a component of a distinct variant of Decision Support Systems (DSS). This DSS leverages an amalgamation of data mining, statistical instruments, and machine learning algorithms to ascertain the probability of specific events unfolding. To illustrate, financial institutions employ AI and machine learning-driven decision support systems to identify instances of fraud. Similarly, insurance companies employ these systems to assess risk. Extending this concept, universities have the potential to adopt and implement such systems to enhance their decision-making processes (Teng *et al*., 2023).

1.8 Design, Methodology and Ethics

According to Saunders, Lewis, and Thornhill's (2016), ontology is characterised as the exploration or scientific inquiry into the essence and fundamental nature of reality. This concept is closely intertwined with an individual's intricate framework of beliefs. Hovorka (2009) states that Design Science Research makes use of pragmatic research paradigm to develop innovative artefacts and solve real-world challenges, moreover neither positivism nor interpretivism truly covers design science research (Weber, 2010). Furthermore, studies guided by the pragmatism research philosophy have the flexibility to incorporate a variety of research approaches, including qualitative, quantitative, and action research methods. Design Science Research supports a pragmatic research paradigm that is proactive with respect to technology (Simon, 1996). Goldkuhl (2012) delved into the examination of pragmatism and its underlying epistemological principles as a prospective framework for design research. This study adopted pragmatism as a paradigm due to its inherent ability to seamlessly incorporate multiple research approaches and methods, and because of its suitability to contribute valuable and actionable knowledge in line with respondent’s expectation and, thus offer practical solutions to the selected case study institution. There are diverse factors at play that affect the decision-making process in the university's ICT department, thus, aligning with the above statement relating to a composite of multiple perspectives. Leedy and Omrod (2014) perspective is that epistemology is construed as a method for comprehending and elucidating the way we attain our understanding and knowledge, “how we know what we know ". Epistemology aims to address the connection between the researcher and the subject of their research. This study is informed by a combination of subjectivism and objectivism perspectives; that is, the researcher interacted with participants when gathering requirements specification information, current problems and how they envisage the new system. Johnson and Christensen (2019) posit that in mixed research it is necessary to grasp both objective and subjective perspectives on reality. Interviews were conducted, thus, creating conversations relating to developing a managerial solution. Bell, Bryman and Harley (2022) state that axiology pertains to the researcher's role and the values they bring to the study. In this study, the researcher is involved in the conception of the study and is conversant with and involved in all steps through the completion of the research study. Thus, the researcher is the principal investigator, taking charge of all processes and being accountable for research activities.

1.8.1 Research Design

The research design creates a structural guideline for the researcher regarding theories, strategies, and instruments utilised during the research investigation (Athanasou, Di Fabio, Elias, Ferreira, Gitchel, Jansen and Mpofu, 2012; DePoy & Gitlin, 2015). Regnell *et al.* (2011) suggest that Design Science Research (DSR) is a research method based on outcomes and is frequently used in IS and IT with rules for evaluating and doing iterative testing. That is, a research design holds together different components of the research. Various research designs include case studies, surveys, explanatory, exploratory and descriptive. Each of these designs is determined by the nature of the study, research question and researcher's set of beliefs and values in the collection, analysis, interpretation and use of data (Leedy & Ormrod, 2014). A non-exhaustive list of examples of research designs is summarised as follows:

Action Research: Leedy and Omrod (2014) define Action Research as a study carried out during an activity. For example, research can identify first-year university students who struggle to adjust to the university system and then develop a solution to fix the problem. The solution is implemented, and its effectiveness is evaluated. If the solution produces the desired results, the solution is repeatedly developed until the problem is solved.

Comparative Research: Creswell (2014) states that comparative research designs are used when the focus is to obtain similarities and differences between variables or events as they occur.

Design Science Research: Constitutes a research methodology that centres on the examination of the design process itself (Babbie, 2020). Information Systems researchers design and analyse new artefacts, thus allowing the generation of knowledge about the method of designing an artefact.

Explanatory Research: These designs are widely used in laboratories where experiments are conducted, allowing additional research (Creswell *et al.*, 2011).

Exploratory Research: The focus is to acquire more information on a subject that has not been previously done. In many instances, exploratory research designs allow researchers to start the study with a basic idea and identify pertinent issues for the study through research.

The objective of this study was to develop an AI-enabled decision-support system; therefore, an artefact was produced. Results from the qualitative semi-structured interviews were used to develop an artefact, which was validated by testing the system with dummy data. Participants were approached quantitatively to validate the results and confirm if their inputs were captured correctly. ICT participants' involvement helped verify if the system was meeting the expectations proposed in this study. The ideal research design for this study was Design Science Research (DSR) discussed below.

1.8.2 Design Science Research

The nature of the problem at hand is neither exploratory nor explanatory but requires developing a new system for decision-making at a selected public-funded university. This study involves the design and development of an artefact; therefore, the DSR methodology is used. The current operational decision-making processes at the selected university's ICT department are not synchronised and are done in silos. Thus, the researcher has elicited users' perceptions of the current information systems and how they expect the challenges to be addressed. An AI-enabled solution is designed and presented to participants for their feedback. Feedback from participants is essential to refine the artefact, which is part of DSR.

The DSR approach aims to solve a decision-making problem through an artefact (Livari & Venable, 2009). The nature of the problem under investigation warrants the DSR methodology to produce solutions that would be widely acceptable.

Peffers *et al.* (2007) posit that DSR allows the researcher to create and design information technology (IT) artefacts to solve an organisational problem. In this study, the problem is the decision-making processes done in silos within different units of the ICT department. Therefore, adopting the DSR will help rigorously design an AI-enabled artefact (system) to solve the issue at hand. Hevner, Ram, March and Park (2008) concur by stating that DSR entails an in-depth analysis of the artefact's use and performance. The authors outline how DSR is conducted, evaluated and presented by describing its boundaries and a set of guidelines. Pertinent to DSR methodology is the production of an artefact to solve an organisational problem and improve decision-making. With reference to the objective of this study, the developed artefact will contribute to its application within the context of the university's needs. Therefore, the design construction will contribute to the knowledge base through evaluated methods, constructs and improve design science knowledge (Hevner *et al.*, 2008). Figure 1.7 below will aid in designing an AI-enabled decision support system.

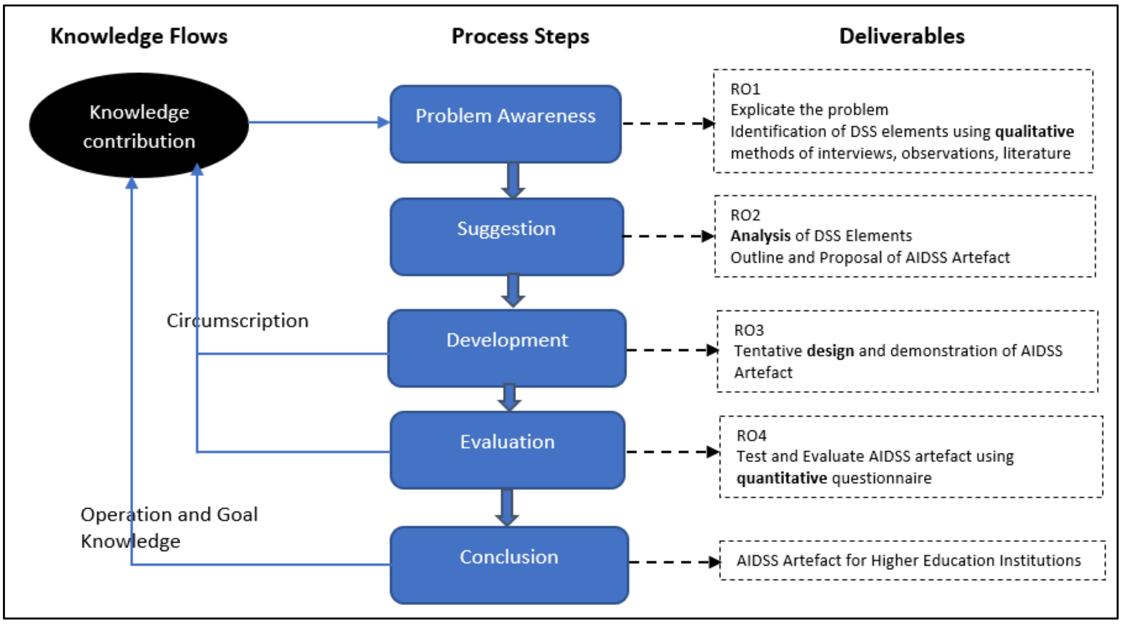


Figure 1.6 AIDSS conceptual framework (adapted from Kuechler and Vaishnavi, 2008)

The illustration in Figure 1.6 above is summarised as follows:

- ***Step 1***: The first step is identifying an organisational problem and motivating why it should need resolution. A clearly defined problem statement will warrant further investigations into its effects if it remains unresolved. Researchers can read from recorded works and literature to better understand the problem's nature. The problem in this study is the inability of management and employees to make informed decisions based on the current decision-making processes, which are fragmented due to disparities in systems and copious amounts of data.
- ***Step 2***: Defining the objectives of a solution is an essential step for the researcher to decide on a better artefact to accomplish in line with the defined research problem. Problems might require different trials of solutions before the design of an ideal artefact materialises. Step 2 is a solution-centred initiative, a university-wide system that could address operational challenges.
- ***Step 3***: Design and development: The proposed research involves the design and development of a prototype artefact. Users experience the design and presentation of an artefact followed by assessment and evaluation to determine if it addresses the problems raised by users.
- ***Step 4***: Evaluation: In this step, the measurement of usefulness of the artefact against its ability solves the problem and meets the organisation’s strategic objectives. If the artefact fails to meet the expected goals, it can go back to step 3. An appropriate IS project management methodology allows iteration before proceeding to the next step.
- ***Step 5***: Conclusion: the last step of the DSR is to conclude and communicate the results of the developed solution through the lens of scholarly and professional publications. This process entails demonstrating the use of the artefact at the selected public-funded university. If users are happy with the system, then implementation on a full scale commences.

Kuechler and Vaishnavi (2008) state that it is crucial to follow the above steps in their logical order to yield the desired results. While Peffers *et al.* (2007) argue that it is unnecessary to follow the steps in their logical sequence, the nature of the problem at hand may determine how an artefact could be developed.

Given the contrasting views, this research adopted a problem-centred approach because there is an existing problem, and literature concurs with its existence; thus, a logical sequence has been followed through the conceptual framework in Figure 1.6 above. Using Kuechler and Vaishnavi (2008) framework, the researcher was able to investigate the effects of AI on DSS and identify and illustrate any challenges and opportunities that may arise while implementing an AI-enabled DSS to improve decision-making across different departments and teams at the university.

The adopted conceptual framework illustrates the contextual setting of the research project. In the research process, the initial phase involves identifying and justifying an organisational problem while emphasizing the importance of a well-defined problem statement that warrants further investigation. This is followed by a focus on defining the objectives of a solution, particularly when dealing with complex issues that may require multiple solution trials. The subsequent phase involves the design, development, testing and evaluation of a prototype artefact aimed at addressing the identified problem. Evaluation is a critical step where the utility of the artefact is measured against its ability to solve the problem and align with the organisation's strategic goals. If the artefact falls short, it can be refined through iteration, employing suitable project management methodologies. Finally, the research concludes by communicating results and demonstrating how the artefact can be effectively utilised within the chosen public-funded university, with full-scale implementation contingent upon user satisfaction. To achieve research relevance, the project requisites are functional necessities aligned with the organisation's hierarchical frameworks, strategies, roles and characteristics of people working within the university. It is acknowledged that predictive decision-making processes are the nexus of this study; however, the technology infrastructure, applications and capabilities were examined to determine how AI tools could be used to improve predictive decision-making. The outcome of this project will contribute to the design of the artefact and design construction.

1.8.3 Evaluation of the study

The effectiveness of the artefact must be measured to establish if there is an improvement in the operational decision-making process at the ICT department; therefore, a Goal Question Metric (GQM) approach as per Figure 1.7 below, was used to evaluate the artefact. Caldiera and Rombach (1994) posit that the GQM approach necessitates that the researcher clearly defines the objectives of their research project, establish a connection between these objectives and the relevant data that will help achieve them and create a framework for analysing and interpreting this data. Three levels for the GQM are:

- ***Conceptual Level***: involves clearly defined all goals for the project.
- ***Operational Level***: includes development of a set of questions for investigation.

- ***Quantitative Level***: datasets require subjective or objective focus on the research questions.

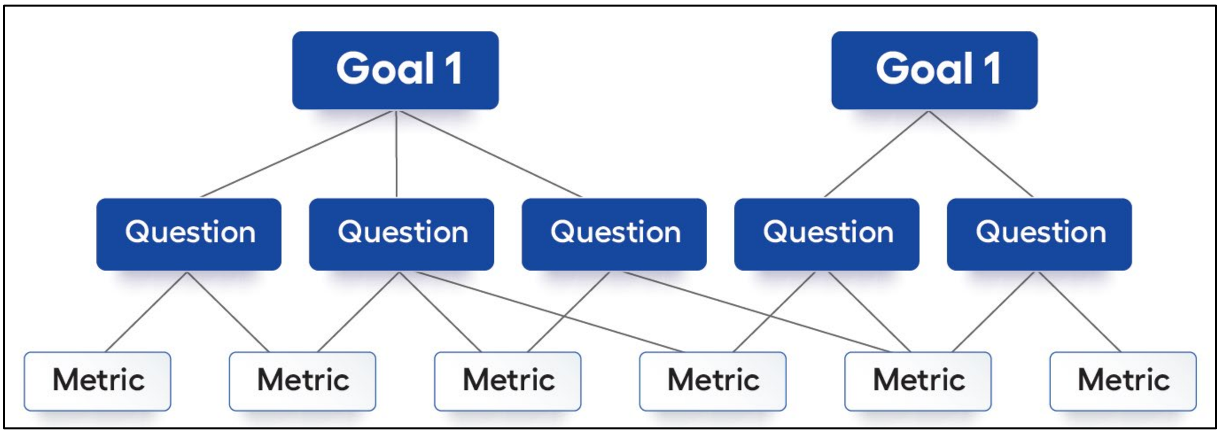


Figure 1.7 Goal Question Metric Model (Caldiera and Rombach, 1994)

As discussed in Chapter Five comprehensively, quantitative evaluation methods were applied through GQM to objectively measure the artefact's effectiveness and validate its capabilities. This data-driven analysis provides concrete evidence of the artefact's success and served as a crucial foundation for its development.

1.8.4 Data Collection in DSR

In this study, the collection of data for constructing an artefact can draw from either the surrounding environment or the established knowledge base, as expounded by Hevner *et al.* (2008). Regarding the environment-based approach, DSR can employ data collection methodologies that are commonly employed within the realm of Information Systems research, such as observation, interviews and questionnaires. In contrast, the selection of theories for theoretical framework and systematic literature reviews would be ideal data collection extraction techniques if the knowledge base is to be used. For this study, questionnaires, observations, and interviews were conducted to extract data from decision-makers in the ICT department. Saunders, Lewis and Thornhill (2019) state that observations are used to study people's behaviour whilst in action.

The four areas of data collection using Hevner *et al.* (2008) conceptual framework are:

- ***Data Collection Area 1***: This entails establishing the requirements from the problem domain for building and evaluating the artefact.

- ***Data Collection Area 2:*** This is when the consideration of available knowledge contributes to assisting the building of the artefact.
- ***Data Collection Area 3***: The existing environmental practices consider assisting with the building of the artefact.
- ***Data Collection Area 4***: The evaluation of the artefact occurs in a lab environment and, if possible, in the organisational environment to demonstrate its utility, efficacy and quality rigorously.

1.8.4.1 Data collection during requirement elicitation

DSR approaches are ideal for wicked problems which emanate from the environment base. As pointed out above, this study is informed by the subjective and objective epistemological perspective; the researcher has immersed and conversed with participants when eliciting information regarding current problems and what users expect from the new system. The researcher for this DSR study collected data from participants through semi-structured interviews to confirm the organisational requirements of the environment. Confirmation of the problem is possible through one or a combination of observation, interviews and questionnaires. In this study, the researcher is part of the research site; therefore, a case study observation was used to confirm the ICT departmental need and assess how users make decisions in a real-life context. This gave the researcher an understanding of how things are done and why specific decision problems are experienced. Since there are different information systems, The researcher engaged in interviews with fellow participants within the case study setting to corroborate the essence of the issue at hand. Their inputs played a pivotal role in shaping the approach to the solution. Saunders *et al.* (2019) state that face-to-face interviews allow conversations and probing for clarity. Thus, in this study, participants clarify the nature of the problem from their understanding and how they have been affected.

1.8.4.2 Data collection during design: knowledge contribution

This is the second data collection phase; however, this phase comes immediately after establishing the requirements for the artefact. Smuts and van der Merwe (2020) state that the design process uses heuristic strategies to produce feasible designs to address the managerial problem. The initial step in data collection for this process involves the researcher exploring the knowledge base and understanding how existing knowledge can be applied to address decision making challenges. There are two approaches that can be taken; utilising existing theory to create a framework for developing a solution or conducting a review of literature and extracting relevant knowledge through textual analysis or systematic literature review. According to Smuts and Van der Merwe (2020) when existing theory is employed in developing the solution it leads to the creation of a framework. On the other hand conducting a literature review involves comparing results from various studies and incorporating data from these studies into building the solution.

1.8.4.3 Data collection during design

An artefact can be created when the researcher is involved in data collection in the environment (Smuts & Van der Merwe, 2020). This process focuses on looking at cases with existing solutions implemented to address a similar problem. In this phase, the researcher observes the university's decision-makers in action (access to the environment). This helped the researcher to see how things are being done and thus, capture these actions as best practices as a solution for the artefact. Interviews were used to obtain participants' opinions and perceptions about the problem. Interviews provided the researcher with flexibility to ask questions. In chapter three, the researcher expanded the data collection process as well as the research methods used in the study.

1.8.4.4 Data collection through the evaluation of the artefact

Evaluation of the artefact is the final activity. Hevner *et al.* (2008) state that evaluation is a crucial guideline; thus, the process should define appropriate metrics. Evaluation commences once the requirements and constraints of the problem are met. In this study, the developed artefact was tested using live data to determine if it meets user requirements specifications. If the system does not meet the requirements, it is refined until it meets the user's expectations. Evaluation can be conducted either through an assessment, where the solution is tested in a realistic manner or in an actual environment (Smuts & Van der Merwe, 2020).

1.8.5 Ethical Considerations

Any research study involving people should consider ethical issues to avoid legal battles. For example, if participants do not give consent, the researcher can be challenged in court that the participants were forced against their will. Before undertaking the study, the Cape Peninsula University of Technology approved the study and granted ethical approval. The selected public university, which is the research site for the study, was then approached for the gatekeeper's permission to collect data from its staff members. These approvals enabled the researcher to identify the following issues that emerge throughout the research journey:

- ***Full Disclosure of Study Information****:* The introductory narrative to the participants included the researchers name, surname and contact information. Moreover, it provides a clear explanation of the research project's aim and objective to ensure participants were well informed. This gave them the choice to either continue or opt out of the study.
- ***Privacy and Confidentiality***: The creation of the research tool intends hiding any personal details during the interviews. Concerning Section 26 of the Protection of Personal Information Act (POPIA) of 2013, no sharing personal information or responses occurs without obtaining expressed written consent from the participants. Shared information is private and confidential.
- ***Participation in the Research is Entirely Voluntary****:* Participation in the study is voluntary without any coercion. There are no rewards or incentives for participation; thus, participants are free to disengage from the study at any time without consequence.
- ***Integrity and Honesty****:* The main duty is to ensure the safety of all participants and create an environment of trust by promoting honesty and preventing any form of misconduct or inappropriate behaviour. Assurances guarantee participants that the principles of integrity underpin the current study.
- ***Inducement to Participate****:* The concept of inducement as defined by Ngulube (2014) refers to the act of persuading or guiding someone to take actions under conditions. The information participants provide is entirely voluntary to avoid incidences of inducement. It is possible for the confidential collection and recording of participant details on an individual form. However, the demographic details of the participants in this study did not include any information. Additionally, the disclosure of participant names or the organisation they work for remain anonymous to protect their information. This approach adhered to the regulations outlined in the Protection of Personal Information Act (POPIA). The identity of the selected HEI and the participants were anonymous. With reference to the positions and or profiles of participants, it was imperative to have this inclusion/exclusion criteria because certain groups of people with knowledge were required to participate in the study.

1.9 Delineation

The study focuses on developing an AI-enabled decision-support system for South African HEIs. The investigation was done at a selected university in Eastern Cape, South Africa, as a case in the ICT department. Elements affecting ICT department operational decision-making were considered, emphasising forecasting improvement techniques using Artificial Intelligence. The selected university deals with Big Data; therefore, management and employees should extract essential information to make informed decisions. Thus, this study did not consider the other types of data, networking, information security, IT infrastructure and programming components.

1.10 Outcomes, Contribution and Significance

This section discusses the outcome, contribution and significance of the study. The primary outcome of the study is an AI-enabled decision support system which might be a benchmark for public universities in South Africa. The study contributes to the body of knowledge by developing an Artificial intelligence-enabled decision support system artefact.

The study explains and expands theoretical understanding of Artificial Intelligence, IDSS and the Fourth Industrial Revolution technological advancements. The theoretical contribution of this study lies in the use of DSR to design an artefact for solving a decision-making problem in a public-funded university. The proposed solution could help improve the decision-making process in the ICT department. This study used a mixed-method approach that involves multiple data collection techniques to inform the DSR/designing of an artefact. Data was collected using qualitative and quantitative methods resulting in the design and development of a new AI-enabled decision support system for decision-making in the ICT department. The questionnaire was utilised for quantitative data, and the results were analysed and interpreted using SPSS software. In contrast, interviews were used for qualitative data, and the results were analysed using thematic analysis. The study has developed a prototype to solve the decision-making problem at the public-funded university's ICT department. Implementation of the proposed solution was evaluated using the DSR iterative process to determine if it meets user expectation.

The study's significance lies in the aim that it will be helpful to several people, including employees and management, as the ICT department could provide services promptly, efficiently, and with a higher level of quality using the proposed AI-enabled DSS. The developed intelligent system for the study should relieve ICT support personnel from monotonous tasks while minimising downtime of operation services. In so doing, the ICT department could provide high customer satisfaction and cost-saving for the HEIs. Subramanian *et al.* (2022) contend that "intelligent, services-based, event-driven, process-automated, data-centric systems" may also provide customers and the IT team with accurate and timely service reports, which will allow them to observe services in real-time. The conclusion and recommendations will be helpful to a wide range of readers. This study provides a practical application of decision-support systems, which could add to the scholarly research on the phenomenon inside South African Universities. By constructing streams of study domains in IS, the findings may help guide the structure and integration of academic research on AI in HEIs. The recent studies are context, practice-oriented and informational documents; consequently, this research contributes through scientific investigation of empirical IS studies. The study findings will aid policymakers in forming judgments on IS, particularly in higher education institutions.

1.11 Outline of the Chapters

The Introductory Chapter One of this study presents the rationale behind the research, providing a comprehensive background and description. It highlights the problem statement, identifying the specific research gap to be addressed, and the research objectives that will guide the study's direction and focus.

The Literature Review chapter of the study concentrates on the convergence of ICT within Higher Education Institutions, examining the research environment and introducing the case university's ICT operations as a comprehensive perspective. Additionally, it delves into the operational decision-making process within HEIs, aiming to provide a comprehensive understanding by analysing factors, frameworks, and approaches that influence and shape decision-making in higher education institutions. It explores decision-making models, information sources, decision criteria, and stakeholder involvement through relevant literature.

In the Research Approach and Methodology Chapter, the research process is discussed, encompassing data collection, analysis methods, theoretical framework, and the approach taken for interpreting the data to address the research questions.

Results Chapter presents the research data, influenced by the research philosophy, and reports on the empirical findings from the interviews and observations. Furthermore, it introduces the proposed artefact, which is developed based on the data analysis.

The Artefact development Chapter discusses the processes and steps that were followed in developing the artefact/

In Analysis and Findings Chapter the artefact is evaluated through a questionnaire and Goal Question Metrics to assess its effectiveness.

Conclusion Chapter serves as a comprehensive conclusion, assessing the fulfilment of research aims and evaluating whether the stated problems have been addressed. It also identifies any potential issues that may necessitate further research.

These Chapters guided this comprehensive study on the development of an AI-enabled decision support system and served as the roadmap for navigating through the research, offering a structured and coherent framework to address the research questions and objectives.

1.12 Chapter summary

The focus of the research was clearly defined to provide guidance for the intended goals and objectives. The brief review of existing literature covered areas within the scope of the study revealing gaps in both the matter and related fields, which helped put the current study into context. In terms of research methodology careful selection was made regarding methods, approaches and techniques to ensure their suitability in achieving the study’s aims and objectives. The ethical aspect outlined a code of conduct followed throughout the research process serving as a guiding framework for the researcher’s behaviour and aligning with the purpose of the study. The significance of this study explained its impact including its rationale. Furthermore, it highlighted how this research contributes to methodological and practical advancements. The next chapter reviewed the integration of ICT in Higher Education Institutions, examining the research environment and introducing a case university's ICT operations. It also delved into decision-making processes, analysing influential factors, frameworks, decision models, information sources, and stakeholder involvement within HEIs. The chapter also covered AI in higher education and its impact on ICT decision-making.

CHAPTER 2: LITERATURE REVIEW

2.1 Introduction

The introductory chapter introduced the study, the research problem, the research aims and objective, and other pertinent topics. The background in chapter one highlights the importance of artificial intelligence (AI) in higher education institutions (HEIs) for decision support. With the emergence of Covid-19, HEI operations, including in the case university have undergone a radical change, highlighting the disruptive effects of technological innovations or lack thereof, primarily for decision support. The focus of this study was to address the challenges that both managers and employees face when making informed decisions in the ICT department. The decision-making processes suffered from fragmentation due to differences in systems and the presence of amounts of data. As a result, decision makers struggled to access, integrate and process information effectively. The university's lack of a decision-making framework hampered its ability to fully utilise data resulting in missed opportunities. Dealing with data added complexity to the problem as traditional approaches were not sufficient for providing accurate insights.

The chapter comprises three sections. Section one focuses on delivering an understanding of how ICTs influence global organisations in a broader context. It explores how ICTs have influenced and shaped various aspects of organisational functioning worldwide. The section is important for the case university as it suggests that ICTs play a crucial role in shaping and influencing distinct aspects of organisational functioning on a global scale. These sections formulate and substantiate the main research question: "*What are the various decision-making elements that affect decision-making within the ICT department at the university?*"

The second section delves into empirical studies, evidence, and observations conducted by scholars from different countries. This section focuses on the connection between AI, its typology, use and application in higher education institutions. First the concept of Artificial Intelligence is discussed. Thereafter, the challenges and opportunities are explored in relation to the third research question "*What challenges are decision-makers facing when making operational decisions within the ICT department at the university*?".

The third section examined the body of literature, the main aim is to gain a deep and varied understanding of the Artificial Intelligence and Decision Support field. This pursuit is guided by the study's aim of developing an AI-enabled decision support system specifically designed for the ICT department of the case university. Artificial Intelligence (AI) is rapidly transforming various industries and sectors, including higher education institutions. One area where AI has gained significant attention is in the ICT operations of higher education institutions. AI is altering HEIs, which calls for a succinct summary of the skills that HEIs must employ for decision making, administration and operations (Taneri, 2020). This part of the study is mostly about reviewing relevant literature, which is important for learning more about decision support systems (DSS) and understanding it better. Decision support systems can be leveraged to streamline and optimise various processes within ICT, such as network maintenance, system updates and user support. In this third section the second research question was explored: "*How is operational decision-making performed within the ICT department at the university*?". Thus, this section aimed to provide a comprehensive understanding of how decisions are generally made by examining the factors, frameworks, and approaches that influence and shape operational decision-making in HEIs. By drawing on relevant literature, the section explored various aspects such as decision-making models, information sources, decision criteria, and the involvement of key stakeholders in the process of making decisions.

To conclude this chapter the points discussed are summarised. These concluding remarks aim to connect sections of the chapter and provide a framework that enhances our understanding of the crucial role played by ICTs in HEIs.

2.2 Global Overview of ICTs in Organisations

Organisations use ICTs to generate income, which results in increased productivity (Iwanon-Tournier, 2004; Monrozier *et al.*, 2017). As a result of increased knowledge of the environment and more efficient human resource management, the growing use of ICTs in organisations has enhanced and accelerated employee communication, which has led to an increase in productivity (Gorriz & Castel, 2020). ICTs enable employees to memorise and communicate data (Lapeyrat, 2020). It would be helpful to have a positive outlook on the part that ICTs play in the process of economic and social growth. ICTs provide the foundational infrastructure and tools necessary for the development and implementation of AI systems. Thereby supporting the aim of this study in developing an AI-DSS for higher education institutions. ICTs make it easier and cheaper to acquire information at a time when its mastery is crucial to corporate success and the ability to access, modify, and disseminate information affects the feasibility and sustainability of socioeconomic progress. This is because ICTs simplify and reduce the cost of acquiring information at a time when its mastery is crucial to the success of corporations (Loukou, 2012). Multiple studies (Krovi 2013; Marakas & Hornik, 1996; Paré & Sicotte, 2004; Meinert, 2005; Koivunen *et al.*, 2008), among others, have shed light on the influence that

ICTs have on the expansion of organisations. According to Paré and Sicotte (2004), for businesses to maintain their level of competitiveness, they do not hesitate to make significant investments in various technological advancements. ICTs have become increasingly common in businesses as a means of adapting to ever-changing customer requirements. Research on ICTs indicates that the application of these technologies' links typically to socioeconomic development, which boosts the performance of corporations. According to Reix (2013) and Meinert (2005), the more ICTs are utilised, the more effective they are for fostering economic and social growth as well as the success of businesses. This is evidence that these technological advancements continue to have an impact on performance. Despite the widespread use of information in a variety of activities in the contemporary environment, the questionable applicability of ICTs to developing nations prevails. The growth of businesses using ICTs continues to be a topic of intense interest (Gado, 2018). It is essential to investigate the effect that ICTs have on the efficiency of corporate operations as ICTs no longer merely serve as communication or labour-saving tools. Therefore, there is a strong correlation between ICTs and Artificial Intelligence (AI). AI heavily relies on ICTs to process and analyse vast amounts of data, as well as to facilitate machine learning algorithms and deep neural networks. The availability of high-performance computing, storage capabilities, and advanced networking provided by ICTs enables AI systems to train on large datasets and make complex decisions based on patterns and algorithms.

ICTs affect every facet of human existence. assume a critical role across diverse domains, including business, education, and entertainment, as underscored by Pelletier *et al.* (2021). Many people consider ICTs to be agents of change in terms of working conditions, information management and exchange, educational practices, learning approaches and scientific research (Ben Youssef & Dahmani, 2008). In the HEI sector, having access to ICTs in the classroom makes it easier to acquire and apply skills relevant to the 21st century. The use of ICTs improves education and makes it easier for teachers to create effective learning environments. The use of ICTs enables educators to deliver lessons that are not only aesthetically pleasing but also suitable for pupils of varying academic abilities (Wentzel, 2009). The public sector also makes extensive use of ICTs. The application of ICTs in public HEIs and its effect on the efficiency has been the subject of a great deal of research. According to the definition provided by Cooper and Zmud (2012), ICTs deployment is "an organisational endeavour to diffuse acceptable ICTs within the user population." It is common knowledge that advancements in information technology have the potential to radically alter how the HEIs does business. This could take the form of modifying internal processes to boost the efficiency of the organisation, or it could take the form of reshaping relationships with external individuals and stakeholders (Luna-Reyes *et al.*, 2014).

The fact that computers and the internet are currently undergoing a revolution in both society and the economy demonstrates the relevance of ICT in supporting growth. According to the United Nations Development Programme (UNDP) (2013), ICTs refers to any type of technology that has the capability to generate, save, process, distribute or share information. Our network universe consists of a massive infrastructure that includes interconnected telephone services, standardised computing equipment, the Internet, radio, and television. These gadgets are what make up our network universe. ICTs serve as a platform for the exchange of data, knowledge, and information. It is also a tool for the implementation of e-commerce, e-schools, e-government and e-health. ICTs can spur development. The significance of ICTs in promoting growth has grown because of recent technology developments, price reductions, an increase in network accessibility, and an approach that is more user-friendly. According to Funda (2019), ICTs is an essential instrument for organising civil society and making better use of underutilised human resources. ICTs are versatile. Connectivity, empowerment, coordination, and delivery of services are all possible thanks to ICTs and the internet. This infrastructure offers public services that are responsive as well as cost-effective to economically-disadvantaged and geographically remote people. These modern technologies should be imaginative and useful to successfully address the tremendous backlog of educational, health, agricultural, and social needs in developing nations. Because information and communications technology affect factors such as productivity, product differentiation, the timing of competition, and market access, developing countries should implement ICTs to make the most of their competitive advantages and take part in the global economy. Because of recent advancements in web-based ICTs, the availability of software driven services has opened economic growth opportunities for organisations of all sizes whether they are small or large. This is due to the increasing prevalence of internet use. The availability of metered and charged access on a pay-per-use basis provided by service providers supports cost-effective rates. The resultant increase in enterprise adoption results from improvements in system architecture, web-based software, and high-speed networking.

2.3 ICTs for Competitive Advantage

This study aims to develop an AI decision support system, as such, leverage ICTs for competitive advantage. According to UNDP (2013), ICTs can play a role in facilitating the creation of adaptable solutions, for both public and private sectors. These solutions have the capability to enhance the speed and cost effectiveness of delivering goods and services, particularly in the areas of healthcare and education. However, Efendiogu (2001) pointed out that the dissemination of technology and its utilisation of it may be more important for less developed nations. According to Judie (2013), a nation's level of competitiveness is not only dependent on the degree of adjustment of its macroeconomic conditions or on the natural endowments it possesses but also on its ability to effectively cultivate and utilise its assets (human resources, capital, and physical assets). According to Porter (2012), the level of national competitiveness is directly correlated to the productivity of individual companies (continuous increases in value-added). HEIs must adjust their competitive strategies to raise added value. They must make the shift from having a comparative advantage to having competitive advantages, which include pricing, quality, delivery, and adaptability. According to Meyer *et al.* (2014), the ability to remain competitive is dependent on innovative management practices and technological advancements. Increasing the amount of money spent on intangible assets like research and development, software, design, engineering, training, marketing, and management has resulted in a corresponding rise in the level of competitive advantage.

The importance of ICTs lies in the fact that it enables networks to be faster, larger, and more engaging. Improved connectivity between people and markets lowers the overall cost of transactions and speeds up the innovation process (Jabeen & Ishaq, 2023). The advancement of information and communications technology makes it possible for individuals and businesses to capitalize on the economic potential to increase process efficiency, encourage involvement in wide economic networks, and create jobs. AI advancements also drive the evolution of ICTs (OECD, 2014). The need for processing speeds, improved algorithms and advanced tools for analysing data has driven the advancement of ICT infrastructure and technologies. Artificial intelligence (AI) has sparked progress in cloud computing, edge computing and distributed systems facilitating the management and examination of amounts of data (Laudon & Laudon, 2020).

2.3.1 ICTs for Knowledge Economy

ICTs can enable the sharing of solutions, among individuals and communities making it possible to provide access to knowledge, on company bookkeeping, weather patterns and best farming practices. In addition to this, they have the potential to facilitate global connectivity, which may result in the development of new techniques for the production and distribution of goods and services, and they may also grant developing nations access to new markets and competitive advantages, which may stimulate economic growth. By assisting firms in their participation in the knowledge economy, information and communications technology can help reduce social and economic gaps and accomplish other broad development goals. ICTs applications not only improve the management of information and knowledge within an organisation but also cut transaction costs, transaction speed, and transaction dependability for interactions between businesses and between businesses and consumers. They improve the standard of service provided to both new and existing consumers, as well as the quality of communications with the outside world. Organisation for Economic Co-operation and Development (OECD) (2014) mentioned that ICTs as well as online commerce are beneficial to a variety of business activities. The use of ICTs and its applications can improve organisational communication and resource management. The improved facilitation of corporate activities such as paperwork, data processing, and back-office tasks such as order processing and billing occurs due to effortless movement of information. Shared electronic files and computers enable these processes which connect through a network. OECD (2014) explained that newer forms of technology give companies the ability to store, share, and apply their acquired expertise. Managers and employees can give greater customer care because of customer databases that include past correspondence. The data in electronic form affords the sharing of professional experience of employees via organisation-wide distribution channels. Jabeen and Ishaq (2023) argued that the Internet and e-commerce might reduce the costs of conducting business with companies, as well as increase the dependability and seed of such transactions. They reduce inefficiencies caused by a lack of coordination in the value chain. The reduction of information asymmetries and the establishment of relationships with commercial partners are both aided by real-time communication and business-to-business interactions that take place over the internet. Using e-commerce can cut down on transaction costs, boost transaction speed and reliability, and raise the value of value chain interactions, according to the OECD (2014). Electronic storage and sharing of client feedback and employee professional experience can help a firm better respond to the needs of its customers by using the expertise of both parties. Some companies have implemented ICTs to improve their internal communications and reputation by more quickly responding to customer complaints and determining what their customers want. The use of ICTs will lead to greater efficiency. If businesses are unable to keep up with the rest of the developed world in terms of technology, productivity growth may slow. This study identifies dynamics and challenges posed by emerging technologies, which may lead to changes in the workplace and organisational structures linked to ICTs.

2.3.2 ICTs Adoption

The adoption and spread of ICTs are both influenced by price and education. Education and training are crucial in establishing a consumer base for digital or informational goods, in addition to offering employment opportunities and manufacturing abilities. A civilisation that is based on knowledge will affect both the global economy and education. According to UNDP (2013), the quantity of information, the vast majority of which is relevant to life and fundamental well-being, is exponentially greater than it was a few years ago, and its growth rate is accelerating. This is the case although most of the information is relevant to life and fundamental well-being. The combination of significant data and communication on a global scale has a synergistic effect. The channelling of this force has the potential to offer constructive application, shaping fulfilment of certain educational requirements. Because of this, both public and private funds will need to invest in new hardware, software, and educational facilities. According to Jide (2009), the information society calls for a workforce that is well-versed in technology concepts. Finding reliable information sources, appropriately accessing those sources, synthesising the content, and discussing it with other people are all required steps in this process. Across Africa, national policies have made it a priority to improve education by investigating new methods of pedagogy and student instruction. According to UNDP (2013), advances in ICTs make education better. The use of ICTs improves education and the spread of knowledge. UNDP (2013) assert that ICTs have the potential to make learning more successful by increasing accessibility, promoting efficiency, and improving learning, teaching, and management systems. The use of ICT makes continuing education easier. ICTs are changing the way HEIs teach. Learning may now take place at a distance. The elevation of HEIs collaboration incorporates a new way to teach, in which students take a more active role. They argued that pupils should have access to ICTs to communicate with one another, create PowerPoint presentations, and engage with both their teachers and their classmates. For nations to reap the benefits of technological advances, it is necessary to have a pool of professionals who are knowledgeable in ICTs. Africa is currently undergoing a phase of witnessing the emergence of new labour patterns, new ideals regarding political involvement and human rights, multicultural societies, and challenges pertaining to the environment, as stated by the United Nations Educational, Scientific and Cultural Organisation (UNESCO) (2012). UNESCO (2012), states that to meet the challenges posed by modern society, individuals and organisations must continue to educate themselves and learn new abilities. Because of globalisation, education is now required to make socioeconomic progress. Education not only prepares individuals for successful lives in the modern world, but it is also necessary to consistently adjust oneself to the requirements set forth by society. This is an opportunity to skip forward to the information era and participate on an equal footing in a global society. According to UNESCO (2012), for governments to fully capitalise on the power of developing information and communications technologies, they are placing a primary emphasis on expanding educational opportunities and improving the overall quality of education. Making use of the potential offered by information technology does not need investing in the most cost-effective hardware and software. It comprises conducting an analysis of requirements and improving procedures. According to Jide (2009), developing countries need to have high-quality human capital in this digital age by enhancing computer skills and knowledge of information technology. Because of widespread poverty and illiteracy, individuals' levels of IT expertise are quite low. Planning for the information and communications technology workforce should go hand in hand with computer education. The use of computers in classrooms should not be voluntary. The process of building an effective strategy and action plan for strengthening one's abilities in the areas of information technology and telecommunications as part of manpower planning is essential to enhancing both the performance of an organisation and its global competitiveness. UNESCO (2012) asserts that information and communication technologies have an impact on the new global economy and help speed up social development. Current information and communication technology tools have completely altered how humans engage with one another and conduct business over the past decade. They have caused changes in the commercial, agricultural, and medical fields as well as in the industrial ones. The use of ICTs has the potential to not only transform where and how students learn but also operations in HEIs. Information and communication technologies can facilitate student access to huge information resources, cooperation, expert consultation, knowledge exchange, and the solving of complicated problems. Students now have access to new tools that allow them to express their knowledge through text, photos, graphics and video thanks to advances in ICTs. According to UNESCO (2012), ICTs have the potential to enhance the learning environment by supplying tools for debate, discussion, collaborative writing, and problem-solving, in addition to providing online support services to facilitate the growing comprehension and cognitive development of students. Multiple methods and procedures exist. Word processing, database management, spreadsheets, and other web programmes are all incorporated into these tactics. The following are examples of multifunctional educational strategies: web-based courses, cyber guides, multimedia presentations, telecommuting projects, online dialogues, virtual classrooms, individualized education, and computer conferencing (UNESCO, 2012).

2.4 South African Overview of ICTs and HEIs

Higher education all around the world, including in South Africa, is adjusting and evolving. The significance of the function of ICTs is paramount. According to Satgoor (2015), most of the financial support for South Africa's education institutions comes from the Department of Higher Education and Training. It is crucial to provide HEIs with financial support. Inadequate funding for HEIs can lead to a variety of problems, including inadequate infrastructure and restricted access to ICTs (Agarwal, 2018). HEIs should try to provide the greatest learning and working environments, including relevant and usable ICTs, to justify considerable government investments in higher education (Agarwal, 2018). The political and socio-economic upheaval that has taken place in South Africa since the country gained its independence in 1994 has led to an increase in the number of underprivileged students and academic personnel. This expected and well-known route through higher education has resulted in the emergence of new difficulties. Students coming from a variety of socioeconomic backgrounds have wildly diverse levels of information and communication technology literacy (Agarwal, 2018). Literature reviews suggest that HEIs in South Africa use ICTs for knowledge management in a variety of diverse ways; however, all these HEIs have benefited from the National Integrated ICT policy, which has enhanced the delivery of ICT services (National Integrated ICT Policy, 2014). In this context, HEIs in South Africa have incorporated information and communication technology and improved access to information. ICT has facilitated the expansion of South Africa's cities and rural areas (Statistics South Africa, 2012). In addition, the government of South Africa has taken steps to make the internet more readily available. Connectivity to the Internet has been beneficial to many students pursuing higher education, particularly those participating in distance learning programmes. According to Merrill (2017), the use of ICTs in HEIs has the potential to enhance operations, teaching and learning. Because of the problems outlined above, HEIs in South Africa make significantly less use of ICTs than institutions in other countries, such as the United States (Agarwal, 2018). As per Satgoor (2015), the infrastructure of ICTs has provided chances for knowledge management at South African HEIs. These opportunities include easy communication and access to education. ICTs are utilised inside educational technology to enhance and simplify the learning process. They are utilised in the production of course material, the organisation of information, and the establishment of connections with students and teachers (Sarlak & Forati, 2015). ICT is utilised to a significant degree by academics working in HEI so that they can remain current with the most recent breakthroughs in every subject. This includes accessing copious amounts of information and knowledge stored in institutional repositories, building capacity and transitioning to the virtual and online resources and services offered by the internet. The availability of information has helped the personnel work together more effectively. The employees' capacity to provide dependable and valued services is improved by the ICTs infrastructure because of the employees' engagement with huge quantities of information. The selected case university can leverage ICTs for operational improvement. By strategically adopting and integrating ICT solutions, the case university can enhance efficiency, accessibility, and effectiveness in various aspects of its operations, ultimately contributing to an improved user experience and the overall success of the institution.

2.5 Use of ICTs Among HEIs

Higher education has changed all over the world because of the use of ICTs in fields such as business, medicine, engineering, law, and social studies (Mazhar *et al.*, 2022). Utilising a wide variety of software programmes that are specialised for individual academic fields, collected and organised information spreads across the world's institutions of higher learning (Saif *et al.*, 2022). The use of technology facilitates education, indicating reasons for the proliferation of ICT courses (Drossel, 2017). While they are students, graduates of higher education institutions need to gain crucial ICTs skills to be competitive in today's world (Hew and Tan, 2016). More young people have been able to enrol in college as a direct result of advances in information and communications technology. According to Teo (2015), the increased availability of higher education made possible by advances in information and communication technology has led to a decline in the institution's traditionally exclusive and stuffy qualities (Teo, 2015). Developing countries have a responsibility to ensure that their higher education institutions are ready for the globalisation and ICTs era of the 21st century. The adoption and use of ICTs require supporting infrastructures such as energy and telecommunication connections, however, many African nations do not have these services available to them (Huang, 2017). All these groups — educators, legislators, government officials, and non-governmental organisations (NGOs) — share the goal of elevating their countries' levels of global competitiveness in the information economy. There is abundant evidence pointing to the positive effects of ICTs (Tate *et al.*, 2015). Information systems are utilised by virtually every department to analyse data, improve customer service, and assist in the process of making important decisions that have an impact on the operation and longevity of organisations. According to research conducted, ICTs have not yet established a prominent position in higher education. Even in industrialised countries, ICTs play a supportive role in teaching and learning, as well as in the management of knowledge. As the reliance on ICTs around the globe increases, projected change is inevitable (De Byl & Hooper, 2013). Numerous instruments, methods, and protocols are utilised throughout the higher education sector in the processes of data generation, management, and transmission. In addition to this, they can design, develop, implement, and manage computer-based information systems, notably computer software and computer hardware, to store, utilise, and disseminate data (Wilson & Boldeman, 2012). The global organisation and delivery of higher education have been completely transformed because of developments in ICTs, which have improved access to knowledge as well as communication, cooperation, and teaching (Bhati *et al.*, 2018). Even while ICTs are necessary, its emergence has posed additional obstacles, such as determining which ICTs practices are the best. Higher education institutions in economically developed nations, such as the United States and Western Europe, make significantly more use of ICTs than their counterparts in South Africa and other less developed nations (Bhati et al., 2018). This is mostly attributable to the accessibility of broadband internet, web-based technologies, less priced computer sets, conferencing tools, and ICTs skills in Western Europe and the United States (Bhati *et al.*, 2018).

2.5.1 ICTs for Skills Development

Even in countries with developed economies, there is a wide range of ICTs expertise and application across institutions (Quaye, Harper & Pendakur, 2019). Due to the prohibitive cost of the technology, its deployment requires sufficient finance (Quaye *et al.*, 2019). Students from rural areas in the United States have a greater degree of skill when it comes to information and communication technology than their peers in South Africa and other less-developed nations. Collaborative learning, cybercommunities, and innovative conceptualization and organisation are some of the ways that, according to some experts, information and communication technology might improve higher education (Huang, 2017). In addition to supplying knowledge, ICTs also assists in the development of essential skills (Quaye *et al.*, 2019). Even on a global scale, structural impediments hamper the deployment and utilisation of technology (Teo, 2015). In developing countries, it is difficult to implement and use ICTs in higher education without addressing other economic concerns. Finances pose a significant obstacle (Ozdemir & Abrevaya, 2007). It is common to practise acquiring and implementing ICTs without considering the requirements of the students and staff (Allen & Seaman, 2017). Because of this, there is a possibility that the focus will shift from schooling to ICTs skills (Pegu, 2014). Some students may have a better understanding of technology and get more out of using it; this can lead to a digital gap inside classrooms (Pegu, 2014). Since academics' levels of expertise in technology vary, ICTs may be utilised in a variety of ways across the curriculum. Students can benefit from the content found online, but it may also encourage them to plagiarise (Pegu, 2014). It's possible that the bonding process between teachers and students would suffer because of non-traditional learning environments like online and other non-classroom settings (Mynarikova & Novotny, 2021).

The adoption and utilisation of ICTs in HEI have been hampered on a global scale because of the high cost of both software and hardware. Tate *et al.* (2015) identified five problems related to ICTs in higher education institutions. These are the following: Application design flaws, there are some worries regarding the effect that ICTs will have on education, inadequate administration and the learning curve presented by technology. There are some students and faculty members who are unaware of the assistance provided by ICTs. Some students graduate from HEIs without having made sufficient use of the existing technologies (Tate *et al.*, 2015). Graduate competency profiles need to demonstrate a better degree of ICTs comprehension and expression to meet the demands of the job (Neeru, 2009).

2.5.2 ICTs for Teaching and Learning

In HEIs, despite the difficulties, ICTs have resulted in several new opportunities and benefits for both students and teachers. Self-paced instruction and the use of online classrooms, sometimes known as virtual colleges, are gaining popularity all over the world (Neeru, 2009). In HEIs, ICTs should make teaching and learning more effective and enable students to work while they study simultaneously. The use of ICTs has made training institutions more capable and cost-effective for governments, who are stakeholders in education. Facilitating innovative approaches to continuous learning by linking educational institutions and course offerings to newly developed information resources and networking opportunities. ICTs are utilised in the production of course materials, the dissemination of content, the outlining of curriculum, communication between students and teachers, the delivery of classes, and the conducting of academic research (Granadoes *et al.*, 2019). E-learning is becoming increasingly popular all over the world as a means of keeping up with the latest developments in any field (Altbach *et al.*, 2020). E-portfolios, cyber-infrastructure, digital libraries, and online learning object repositories are all web-based features. The use of ICTs can improve integration, interaction, and participation. These bring together various parties involved in schooling and provide children with a digital identity (Bhattacharya & Sharma, 2017). Despite the difficulties that come with implementing and making use of ICTs in HEIs, these technologies have resulted in the creation of several opportunities, such as the eradication of traditional learning borders (Esteban-Navarro *et al.*, 2020). HEIs all around the world are looking to improve their ICTs skills since the benefits outweigh the drawbacks. The findings also suggest that ICTs have not yet reached their full potential (Esteban-Navarro *et al.*, 2020).

The field of ICTs has shifted its focus away from analogue and toward digital knowledge-based technological advancement in education. According to Akindoju *et al.* (2014), the responsibilities of HEIs academics include teaching, conducting research, publishing their findings, grading student assignments, supervising student research, advising students, participating in professional conferences, and providing community service. They need to know ICTs to be effective. Most teachers in Europe make use of various forms of technology to enhance the presentation of their lessons. The ability of teachers to interact with students and work together is improved using ICTs. According to Osakwe (2013), the use of ICTs can improve the efficiency of teaching, enable the creation of lesson plans, and gather and assess data on student achievement. Additionally, it can help academics keep better records of their work (Akpan, 2014). The use of ICTs is critical to the success of academics in their jobs. The advent of recent technologies has created new vistas of opportunity for educators but has also increased the pressure placed on academics and students to make effective use of the available technical tools in the classroom (Yusuf, 2005). The integration of technology into educational settings opens numerous doors for both teaching and learning. Motivation to learn and develop skills through the integration of technology into the classroom, leads to better prepared students – ready for the demands that await them after their resultant graduation. The transformation of the learning atmosphere in the school and the provision of academics with additional resources contribute to a deeper sense of connection between the educational institution and the surrounding neighbourhood (Akpan, 2014). The information age requires talents – enhanced by inspiration, with technology as a source of inspiration. According to Wright *et al.* (2017), ICTs give students the ability to successfully attempt, identify, set up, and freely communicate with academics, acquire assignments and receive electronic responses, and engage in and initiate online discussions. Considering the above, the ICT support department plays a vital role in maintaining and troubleshooting the systems, providing user support and training, integrating systems and managing data, overseeing technology upgrades and innovation, managing IT infrastructure and resources, ensuring security and data protection, and aligning ICT initiatives with strategic goals. By efficiently addressing technical issues, assisting users, managing data flows, and staying updated with technology trends, the ICT support department enables smooth operations, enhances productivity, and maximises the value derived from information systems throughout the organisation.

2.5.3 ICTs Requirements

The institution should request ICTs and other emerging technologies to satisfy the information requirements of the teaching staff and the student body. Both students and staff need to have convenient access to a Wi-Fi connection that is operational. Knowledge in the areas of science and technology is essential to the development of any nation, and teachers play active roles in disseminating such knowledge (Okolocha and Nwadiani, 2015). According to Oye *et al.* (2012), it should be mandatory for all academics in developing countries to undergo initial and ongoing ICTs training. Giving them hands-on experience with computers, the internet, and other forms of ICTs boosts their productivity and efficiency. Training programmes have a responsibility to consider the real-world circumstances of their academics. The government should draft ICTs policies and guidelines so that professors can benefit from them. For integration in schools to be effective, the entirely networked institution provides access to multimedia and training-rich materials via the internet and intranet of the schools, regardless of where the students and teachers are physically located (Oye *et al.*, 2011). The school requires a suitable number of computers in both the computer laboratories and the study rooms. It is possible that simply having awareness skills is not enough; nevertheless, having constant access to ICTs facilities might enhance teachers' confidence, allowing them the guts to experiment and effectively integrate ICTs into lessons. The use of ICT's allows for data and information access, retrieval, conversion, storage, manipulation, and display (Ololube, 2015). Numerous studies have shown that the use of empowering ICTs improves both teaching and learning for both students and teachers. Researchers have shown that the use of ICTs can improve student learning and education (Wright *et al.*, 2017). The convergence of ICTs has had a considerable influence on the educational system by producing several tools that improve both learning and teaching. In a wide variety of fields, teaching and learning can benefit from ICT's support. Eben (2019) also found that the use of appropriate training, materials, and support can significantly improve the effectiveness of educational technology (ET) resources in the classroom. The use of ICTs resources has the potential to cater to the specific educational requirements of each student, encourage equal opportunity, supply educational content, and facilitate learning through interdependence. Trainers of today and tomorrow need to be familiar with ICTs and deliver technology-supported training for other trainers.

2.6 ICTs and IT Service Management

IT Service Management (ITSM) is a subset of Services Science that focuses on the provisioning and upkeep of information technology services. ITSM emphasizes a process-based strategy and continuous development; also, one of its essential characteristics is the pairing of qualified personnel with process jobs (Orand & Villareal, 2011). A combination of informatics, operations research, business administration, social, cognitive, and legal disciplines in ITSM generate excellent customer service by satisfying the needs and expectations of customers Open Geospatial Consortium (OGC, 2017). Bon *et al.* (2017) clarify that ITSM refers to the process of deploying and managing IT services with a focus on the business. It emphasizes a lifecycle approach to ICTs management and methodologies of ICTs organisation (Galup *et al.*, 2019). ITSM emphasises the importance of protocols and their continuing development (Galup *et al.*, 2019). According to Gartner's research, improper procedures (70% of the time) or incompetent employees (10%) often cause the failure of an IT service. Cox, Marriott and Seabrook (2003) argue that faulty software or hardware causes 20% of unsuccessful attempts to provide an IT service. One of the most important strategic focuses in information technology management nowadays is on the customer (Hochstein *et al.*, 2005). To better support customers with company activities, businesses need to effectively manage service delivery. Establishing a shared understanding between a customer or user and a supplier is a requirement for businesses. The regulation of customer's or user's service-level expectations and delivery, as well as by offering and supporting anticipated results accomplishes satisfactory outcomes. It is necessary to provide a comprehensive description of IT services to facilitate collaboration between providers and customers. Hochstein *et al.* (2005) explain that service providers and customers negotiate terms of service and quality specifications within the context of a service-level agreement (SLA). Global use of IT service management has become a reality. Recent studies indicate that an IT service provider can reduce expenses by as much as 48 per cent by applying ITSM principles, as stated at Microsoft's 2004 IT Forum Conference. According to Forrester's findings, Information Technology Infrastructure Library (ITIL) use is on the rise. ITSM is a concern that involves the planning and management of services including hardware and software installation, network and system administration, application management and help desk support. The implementation of these services focuses on their impact and on business processes. Because IT support and delivery account for 80 per cent of infrastructure expenditures, IT service management places its primary emphasis on these two areas (Fleming, 2015). According to Galup *et al.* (2019), ITSM is a process-oriented management method. The findings of Galup *et al.* (2019) suggest that ICTs bolsters both the functions and requirements of businesses. The performance of a perishable and immaterial experience for a co-producer customer is what we refer to as a service. Measurement of services is a key component of ITSM, which is a subset of Services Computing Science (Zhang *et al.*, 2018). A substantial number of providers of information technology services find it challenging to quantify ITSM processes, in particular service-support procedures. IT companies do not have a standardised evaluation methodology for the services they provide or the methods they use to manage those services. Accurate measurement is difficult or impossible due to the instruments used by service support staff. Rudd (2014) affirm that standards and frameworks for IT service management generally lack realistic examples for assessing support operations. According to Galup *et al.* (2020) IT service management provides principles, methodologies, and measurements for analysing, planning, and implementing IT service operations to maximise both the tactical and strategic use of IT assets. The case institution uses ITIL in various ways to enhance its IT service management practices such as:

Service Desk Management: Enhancing the service desk for handling IT-related incidents, service requests and inquiries from students and staff. This includes incident management, problem management to ensure timely resolution of issues.

Change Management: Managing changes to their IT infrastructure and services in a controlled and systematic manner. This involves assessing the impact of proposed changes, obtaining approvals, scheduling changes during low-impact periods, and ensuring proper communication with stakeholders to minimise disruptions.

Asset Management: Managing IT assets, including hardware, software and licenses. This includes maintaining accurate records of assets, tracking their lifecycle, optimising asset utilisation and ensuring compliance with licensing agreements.

By adopting the principles of ITIL at the case university, the ICT department strives to empower both staff and students to meet the demanding standards required in today's competitive world. Moreover, the aim is to align with the University's strategic plans and goals, ensuring that the necessary technological infrastructure and support are in place to facilitate academic and administrative pursuits. The case university can benefit from an Artificial intelligence-enabled decision-making support system to streamline the above mentioned ITIL principles. For example it can augment service desk operations by using natural language processing (NLP) and machine learning algorithms to automate responses to common inquiries, categorise and prioritise incoming tickets and suggest resolution steps based on historical data and knowledge bases. This can streamline support processes, reduce response times and enhance user satisfaction. Considering this background, Table 2.1 below describes decision-making elements for HEIs.

Table 2.1 Elements of decision-making

Elements	**Descriptions**	**Sources**

Available information	The quality and quantity of information available can impact the decision-making process. If the information is incomplete or inaccurate, it may lead to suboptimal decisions.	Galup *et al.* (2019;2020),
Time Constraints	The time available to decide can impact the decision-making process. For quick decisions, it may limit the amount of gathered and analysed information, leading to a more intuitive decision-making approach.	Rudd (2014); Hochstein *et al.* (2005)
Stakeholder Perspectives	Perspectives and concerns of the individuals involved can influence the decision-making process. When stakeholders have varying priorities or conflicting opinions it becomes difficult to achieve an agreement.	(Orand & Villareal, 2011). Galup *et al.* (2019;2020),
Organisational Culture	The organisational culture can impact decision-making by shaping the values and norms that guide decision-making within the ICT department.	Eben (2019)
Resources	The resources available, including budget and personnel, can impact decision-making by limiting the available options and influencing the decision-making process.	Galup *et al.* (2020)
Risk Tolerance	The decision-making process within the ICT department can be influenced by the level of risk they're comfortable with. When the department has a tolerance for risk it often results in adopting cautious and conservative approaches to decision making.	(Wright *et al.*, 2017). Rudd (2014)

Decision decision-making in the university's ICT department involves considering various factors. These include available information, which informs decisions based on data and insights. Time constraints play a crucial role, as decisions often need to be made promptly to address IT issues or implement changes effectively. Stakeholder perspectives are also important, as the needs and preferences of users must be taken into account. Organisational culture influences decision-making approaches and the acceptance of new technologies or strategies. The availability of resources, including budget, personnel, and technology, determines the feasibility of proposed initiatives. Additionally, risk tolerance guides decision-making by weighing potential risks and rewards associated with different courses of action. By considering these elements holistically, the university's ICT department can make informed decisions that align with organisational goals and priorities. By understanding these decision-making elements, the ICT department at the HEIs can make informed decisions that are well-suited to their needs and objectives. It is important to carefully consider each of these elements to make decisions in a responsible, effective and efficient way.

2.7 The Concept of Decision-Making

Operational decision-making within the ICT department is a crucial process that involves selecting the best course of action from assorted options to address operational and administrative challenges. When we discuss "decision-making," it entails the cognitive process of choosing the most suitable option aligned with specific goals or problem-solving needs (Obi, 2014). Decision-making involves interaction and evaluation, from recognising the need to tackle a problem to finalising a plan to address it, with decisions influenced by logic, emotions, and political factors (Elbanna, 2006). Managers in the ICT department bear the significant responsibility of making decisions, relying on the gathering and evaluation of pertinent information to ensure effective operational outcomes. Decision-making is a fundamental managerial duty that guides the department's actions and strategies (Greene *et al.*, 2009; Rlson, Zayas & Guthormsen, 2009). The age of AI is now upon us. A popular topic of debate and experimentation is how AI will affect ICT operations and decision-making in higher education institutions.

2.7.1 Factors involved in decision-making

Empirical results reveal that strategic decision-making abilities are affected by attention, memory, thinking, emotion and sentiment (Saloogie, 2019). There are several important factors that influence decision making. Significant factors include past experiences, a variety of cognitive biases, an escalation of commitment and sunk outcomes, individual differences, including age and socioeconomic status, and a belief in personal relevance. Making decisions involves a variety of things. Authors contend that subconscious choices occur. These authors claim that people make decisions without giving them much thought. Franklin’s rule is the name of this tactic. However, due to the necessity for sufficient time, cognitive resources, and full access to information regarding the decision issue, this rule is unable to represent how people make decisions (Shahsavarani and Azad Marz Abadi, 2015). According to the literature, strategic decision-making encompasses three abilities: first, the capacity to locate, predict and capture strategic opportunities by assessing the environment. Second, is the ability to make strategic decisions such as setting a goal and deciding on a business strategy. The third step is to integrate resources by selecting, acquiring, and utilising resources (Milliken and Vollrath, 1991; Wally and Baum, 1994). The study by Schønning et al. (2019) believes the strategic decision-making ability system has three dimensions: strategy analysis, strategy selection, and optimisation, and adaptive and updating capacity. All elements work together to develop and perfect strategic decision-making. By carefully studying rational decision-making variables, a comprehensive and workable driving model is created (Spanuth et al., 2020).

Furthermore, enhancing a person's capacity for strategic decision-making allows one to better understand both the environment's special traits and the ever-changing trend (Bilancini et al., 2019). Strategic decision-making, especially in the realm of environmental sustainability, is the focus of academic research (Bilancini et al., 2019). Since demographic characteristics are mostly related to human capital and theoretical explanations are limited, scholars have begun to study the impact of entrepreneurial and executive team characteristics on the quality of strategic decision-making (Friedman and Carmeli, 2018; Feng et al., 2022). There is evidence from prior research suggesting a link between the aggression, core self-evaluation, and strategic decision-making abilities of the senior management team (Clohessy and Acton, 2019; Gao et al., 2021).

According to Tsuji, Hoogenboom, and Thornton (1998) and RIson, Zayas and Guthormsen (2009) the factors influencing decision-making can be broadly categorised as follows:

- ***Rational Factors***: numerical elements like cost, lead time, and forecasts, among others. Typically, people tend to focus on these aspects and overlook non-quantitative ones.
- ***Psychological Aspects***: People play a role in decision-making. A variety of elements influence decision-making, including the decision-personality, the maker's abilities, experiences, perceptions, values, goals, and roles.
- ***Social Factors***: It is important to have the support of others, especially those who influence the decision-maker. Taking these issues into account lessens opposition to the choice from others.

- ***Cultural Facts***: The environment comprises layers, including those that reflect the cultures of the region, the nation, and the universe. Consideration of organisational culture of the decision-maker should occur. These cultures have an impact on decisions made by individuals and organisations through socially accepted trends, shared values and norms.

2.7.2 Processes involved in decision-making

Among the key objectives of science-based approaches to problems are classification, systematisation, and structuring of themes and translating them into a common language, as well as standardisation. The first and/or most crucial step in undertakings should include understanding the existing circumstances. All subsequent steps and the final decision arrived at may be ineffectual when incorrectly identified problems arise. Even though efficacy indices indicate proper efficacy, whenever a person makes the wrong choice and pursues the wrong aim, they are committing the two primary faults of destructive effectiveness and efficacy (Dymond *et al.*, 2010). As per Figure 2.1, situation identification, option generation, evaluation and selection, follow-up, and execution are the main steps involved in decision-making. The decision-making process works best when the decision-making authority is close to the source of the issue (Shahsavarani and Azad Marz Abadi, 2015).

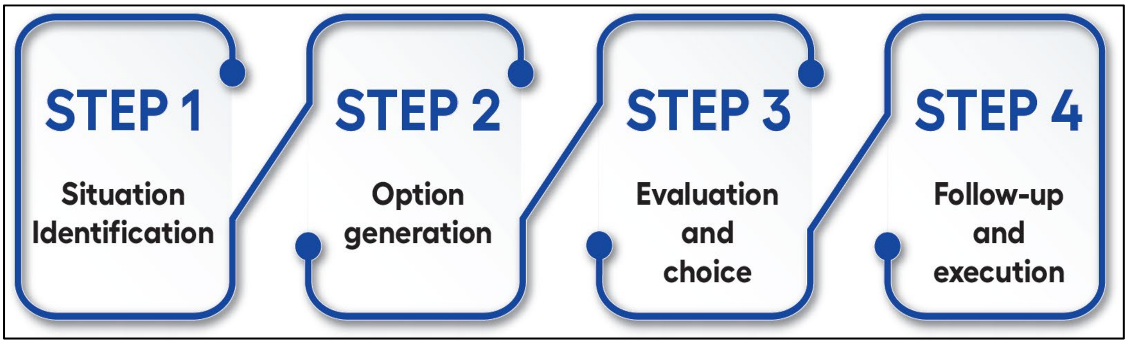


Figure 2.1 Processes involved in decision-making (Shahsavarani and Azad Marz Abadi, 2015).

As depicted in Figure 2.1 for both individual and group (cooperative) levels of decision-making, the deployment of various strategies in arriving at a decision occurs. In individual decision-making, the decision-maker is in charge and the situation under consideration is typically not a matter involving collective issues. The delegation of total decision-making authority to a single person who serves as the head of an institution or organisation, may have an impact on collective destiny (Shahsavarani and Azad Marz Abadi, 2015). Personal decision-making, on the other hand, refers to a decision-making process that includes people. Consequently, differentiated strategies do not depend on consideration of the effects on an individual or individuals (Abad, Jin & Son, 2014). It is important to remember that methods for making decisions on an individual basis may apply in group and collective settings. Due to the constant growth of information and the increasing complexity of its parts, categories, elements, and other related factors, increased people, groups, and businesses need software to help them make decisions (Ozkan & İnal, 2014).

2.7.3 Decision-Making in HEIs

The reputation of a nation's educational system significantly affects its standing on the global stage (Vo & Nguyen, 2012). In this context, Higher Education Institutions (HEIs) bear a substantial responsibility in preparing skilled professionals who contribute to their communities and the nation. Consequently, decisions made at the strategic level profoundly influence the policies, plans, and actions undertaken by HEIs. Directors of HEIs must make challenging decisions that impact not only the academic community but also students, academics, administrators, and the institution's strategic direction. To facilitate this decision-making process, managers within HEIs rely on informative resources. Acevedo and Marín (2015) highlight that contemporary information analysis methods, including data mining, statistics, and social network analysis, have emerged to address information and decision-related challenges at both individual and group levels among students, academics, and the public. Even routine tasks like automated management of attendance lists enhance the efficiency of the decision-making process. Operational decision-making within HEIs encompasses both administrative and academic spheres. Consequently, institutions have implemented computing systems designed to streamline administrative processes. These systems are often organised into distinct departments, such as the Accounting Information System and the Academic Information System. These departments serve as essential components, facilitating the retrieval of data from various sources to support the decision-making process (Acevedo and Marín, 2015).

Advancements in AI technologies offer a significant advantage in this context by enhancing the decision-making process within HEIs. AI tools can analyse vast amounts of data quickly, uncover valuable insights, and provide decision-makers with data-driven recommendations. This enables HEIs to make more informed and strategic decisions, improving the quality of education and administrative operations. AI's ability to manage complex data and provide predictive analytics further enhances its value in supporting decision-making within HEIs. ICTs in HEIs support management but also enhance decision-making. Accounting systems, enterprise resource planning, and academic management are examples of applications of ICTs in HEIs settings (Shuhidan, Mastuki, & Nori, 2015; Noaman & Ahmed, 2015; Anastasios *et al.,* 2013). ICTs infrastructure, usability and level of use impact its influence. Although there has been a substantial increase in computer processing speed and algorithm design, decision-making in HEIs still requires more effective and user-friendly applications. Fortunately, the emergence of machine learning has been a valuable tool in the field of education, since it utilises a range of algorithms to learn from data and support various tasks. This study aims to address a problem by improving the decision-making process, in the ICT department of the selected Higher Education Institution in South Africa. The current decision-making environment within the ICT sector of this HEI faces challenges due to evolving technology requiring decisions that consider unpredictable factors. Therefore, an Artificial intelligence-enabled decision support system will aid the institution in enhancing decision making.

2.7.4 Decision Classification at higher educational Institutions

HEIs currently bear the primary obligation for the oversight and leadership of their revenues, activities, and staff since they retain the autonomy to determine institutional operations. Clark (2005) concluded that institutional governance revolves around determining the individuals accountable for making decisions regarding priorities, strategies, goals and the allocation of resources. As identified by Chan and Yang (2018) the following academic, bureaucratic, and corporate types of governance characterise HEIs and have an impact on management and operational conduct:

- ***Academic Governance***: In areas including instruction, curriculum, academics, and administration, faculty members want to keep their positions of leadership and decision-making power.
- ***Bureaucratic Governance***: The HEIs maintain layers of hierarchy with functional divisions that characterise protocols, set administrations, and direct commands from higher-ranking officials.
- ***Corporate Governance***: The students become the main clients when service-based education is a logical outcome of marketing in HEIs. These primary marketing initiatives help attempts at recruitment and retention (Guilbault, 2018). The practice of enterprise in HEIs contexts emphasises market rivalry and client needs.

In terms of missions and management approaches, HEIs differ significantly; for example, private institutions tend to have a greater emphasis on market-driven and action-oriented approaches, whereas public institutions place a greater emphasis on the social contributions of their students and alumni. However, they all work to promote student success, and HEIs make their choices to make sure of it. Because of this, Jones (2013), has proposed the use of a hierarchical structure to divide work vertically into decision-related responsibilities at HEIs to classify the types of decisions made there and consider their primary objectives across different HEI types. This structure is like an organisational pyramid as presented in Figure 2.2 below.

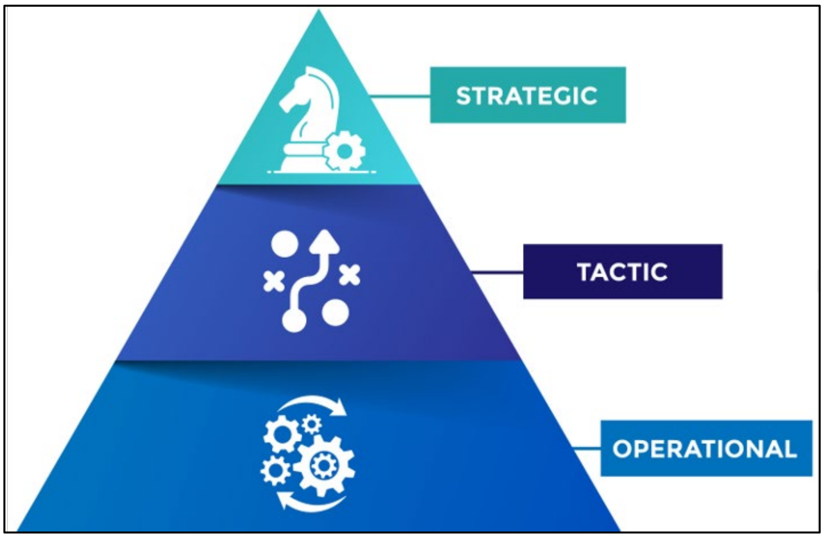


Figure 2.2 HEIs Decisions' structure (Nieto *et al.*, 2019).

The structure encompasses three fundamental levels, the Strategic level, the Tactical level, and the Operational level as discussed below:

Strategic: The highest level establishes the organisation's policies and plans, combining the main objectives and course of action into a unified whole. Tan and Shao (2015) stipulate that those institutions operating at higher echelons exhibit a greater propensity for ambition in their strategic planning endeavours. Positions such as executive board members, principals and deans represent managerial bodies (Hu *et al.*, 2018). In the case university, the Council and Senate operate on this level as per Figure 1.1.The governing board frequently acts in managerial capacities. They talk about the essential elements of strategic planning and offer recommendations for carrying it out. This level of decision-making affects the entire university. The decision regarding the number of new students admitted into the institution at each given intake is one example of the strategic decision made at this level of decision-making in HEIs. The decision made at this level has an impact on how the institution allocates resources. Little to no evidence reports on the use of machine learning algorithms in aiding decision-making at this stage (Yuri *et al.,* 2019).

Tactical: Finding and conducting the specific plans created at the strategic level are the goals of the tactical level. Deans typically collaborate with department heads or program directors to accomplish the planning. Intermediate directors provide management and planning at key moments to efficiently coordinate the use of resources. The tactical level oversees putting strategic planning into action and maintaining control after approval. As a result, at this level, quality assurance is a crucial duty. This middle management makes decisions regarding curricular adjustments and the number of students a teacher can accommodate. In the selected university, the Management Executive Committee and Governance structure, depicted in Figure 1.1, operate at a tactical level. This structure outlines systematic administrative channels, emphasising transparency and efficiency. The use of algorithms ensures quality teaching, evaluation, and timetabling via algorithms like Naive Bayes and Artificial Neural Networks.

Operational: This study aims to develop an AI decision support system at this level. This operational level deals with routine tasks and supports the entire system. To help the institution run, specific tasks and transactional actions take place. This level comprises the information technology required by HEIs. At this point, IT governance serves as a tool for managing and controlling IT resources, including infrastructure, technology, and personnel (Bianchi & Sousa, 2016). Academics, counsellors, tutors, program assistants, secretaries, and other collaborators perform their duties following the directives supplied by the strategic and tactical levels. Decisions made at this level may impact the success of students (i.e., the timetable and timetable evaluation) and operational procedures even if they affect a lesser portion of the HEIs population. According to an analysis conducted by Yuri *et al.* (2019) findings indicate that the operational stage is the focus, for most machine learning projects, within the AI field. Neural networks and support vector machines are two popular algorithms that have witnessed increased usage at this level of decision-making in the HEIs. The operational level is where AI decision support tools can make a significant difference. By leveraging AI algorithms and machine learning techniques, these tools can help IT services to automate routine tasks, analyse complex data sets, and provide intelligent recommendations to improve service delivery. For example, AI decision support can predict and prevent network failures, detect security breaches, and optimise system performance. Moreover, chatbots powered by AI have the capability to aid users by addressing asked questions and resolving typical problems.

2.8 Decision Making Systems (DMS)

A decisional scenario often arises when there are at least two courses of action, but the best choice is unclear. A decision-making procedure manages such a predicament (Mora *et al.,* 2014). The process of making decisions is one of the most crucial and important tasks conducted in organisations irrespective of the industry and geographical context where such organisations are operating (Tzeng & Huang, 2011). There have been frameworks that help with this procedure (Mora *et al.,* 2014). The following of a decision-making process or reliance on tools for making judgments are not necessary for decision makers. However, over the thirty years decision makers have been using decision making methods and computer-based tools known as Decision Making Systems (DMS) to assist with moderate and complex decisions (Forgionne *et al.*, 2009). The development of such a DMS using standard computational tools or improved with clever techniques is feasible. Therefore, the phrase "decision-making systems" can apply to a variety of computer-enabled systems that can be employed in a variety of contexts to offer illuminating cues for making trustworthy and effective decisions. Accordingly, Forgionne *et al.,* (2009), construed DMS to refer to computer-based systems, which provide decision-makers with support throughout stages of the decision-making process. Both conventional and advanced computer techniques may support the implementation of DMS. Sections 2.8.1 to 2.8.3 explore three possibilities.

2.8.1 Executive Information Systems (EIS)

The term EIS emerged in 1980 (Rockart & Tracy, 1982). The researchers highlighted that certain top executives were employing specialised systems to monitor and measure the company's key performance indicators. Accordingly, Rockart and Tracy (1982) defined EIS as a computer-based system that allows access to a database containing internal and external business information, categorised by time and business unit. An EIS typically provides access to summarised data in the form of graphs and text tables allowing for analysis through operations like drill down, rollup, slice and dice pivoting, as networking connections to bulletin boards. These capabilities are commonly associated with an EIS according to Mora *et al.* (2014). Similarly, Azad, Mohammad and Alauddin (2012) provided a definition for an information system (EIS) that describes it as a type of management information system. Its purpose is to assist and cater to the information and decision-making requirements of executives. It accomplishes this by providing access to internal and external information crucial for achieving organisational strategies. EIS places emphasis on interfaces and displays those that are easy for users to navigate. They offer reporting and the ability to dig deeper into the data. In general EIS are systems used by executives across an organisation to analyse, compare and identify trends, in key factors. This helps them monitor performance and identify both opportunities and challenges. It is worth noting that the markets for EIS and data warehousing solutions are coming together.

Initially executive information systems evolved as software that ran on mainframe computers. The idea behind them was to compile business data and provide sales performance statistics or market research insights to decision makers who may not have been well versed in computer usage. These decision makers typically included officers, marketing directors and financial officers. The main objective was to create computer programs that could present information in a way that catered to the needs of executives. Instead of providing data for the entire organisation, an EIS typically simply delivers the information required to support executive-level decisions. The use of EIS extends beyond the conventional corporate hierarchies to individual computers connected to a local area network. EIS now integrates data stored on mainframes, laptops, and minicomputers across different computer hardware platforms. Employees can access company data on their personal computers and choose which facts are pertinent for their decision-making as client service organisations embrace the most recent enterprise information systems. With this system in place all users now can personalise their access to the company's data. Additionally, they can provide information to both level and lower-level members of the organisation (Mora *et al.* 2014).

Executives can utilise EIS to locate and analyse data using user-defined criteria and advance knowledge and understanding based on information. An Executive Information System (EIS), unlike a management information system, can differentiate between data and less frequently utilised information. It also enables executives to monitor actions that play a role in assessing the organisation's progress towards its corporate objectives. Widely adopted EIS applications are evident in industries, including manufacturing, marketing and finance owing to their proven usefulness (Azad, Mohammad & Alauddin, 2012).

2.8.2 Expert Systems (ES)

The initial generation of expert systems emerged from interviews with experts to capture their knowledge, culminating in the term "expert systems." An expert system is a computer program that utilises the expertise of individuals in a field. It performs tasks like asking questions and presenting its reasoning. The user interface of this type of system proceeds with the end user providing questions and answers (Tolun, Sahin & Oztoprak, 2016). Expert systems, also known as knowledge-based systems, are software programs that can perform tasks typically requiring expertise. This has been an area of research in the field of AI for a while and is highly knowledge intensive software (Tolun, Sahin & Oztoprak 2016). Expert systems designed to demonstrate problem solving capabilities, are comparable to those of experts within domains (Mora *et al.* 2014). These systems rely on the guidance and expertise of professionals at each stage of the reasoning process. They serve as systems for problem domains. While widely used AI is evident in applications today, the term “AI” sometimes refers to expert system applications. Since the 1980s expert systems have gained popularity outside research laboratories. Have found applications in diverse fields such as engineering, chemistry, medicine and industry (Tolun, Sahin & Oztoprak 2016).

The knowledge base, the inference engine, and the user interface are the three essential parts of an ES. The knowledge base covers the expert's field. Simple facts or more complicated representations like frames may illustrate it. Furthermore, certain rules explicitly highlight the expertise of the specialist in the field. The inference engine, which serves purposes including determining how the system uses THEN rules in the knowledge base to reason, is employed by the expert system to leverage this expertise. It constitutes the component. With the establishment of the knowledge base, the expert system can begin drawing conclusions. Both forward and backward chaining are types of inference methods. Forward chaining involves progressing from facts towards conclusions derived from them. Conversely backward chaining refers to tracing from a hypothesis to known facts that provide support for it (Tolun *et al.*, 2016).

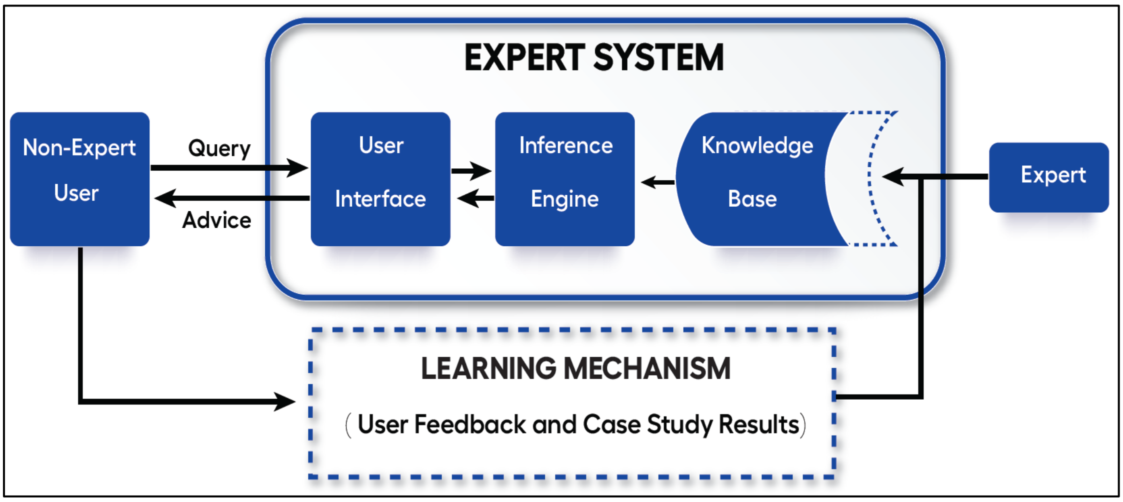


Figure 2.3 The Architecture of an Expert System (Ozden, Faghri, and Li, 2016)

As depicted in Figure 2.3 above, the ES typically addresses two categories of problems—construction and classification. Categorisation issues include concepts like forecasting, maintaining control, diagnosing, interpreting, and repairing. Planning, scheduling, designing, and configuration issues are all related to construction. Intelligent guidance, qualitative reasoning, problem-solving support, and explanation of advice are all features that an ES can provide (Cantu, 1991).

2.8.3 Intelligent Systems

Intelligent Systems (ISs) are subsets of Artificial Intelligence, defined as "any formal or informal system" capable of gathering and processing data, analysing the data using AI and BI technologies, and presenting reasoned judgments to decision makers as a foundation for making decisions (Sharda *et al.,* 2018). Decisions made by intelligent systems can be based on information, learning from previous interactions, and adapting to novel circumstances (Paulovich *et al.,* 2018). Such technologically advanced gadgets have the potential to function in a variety of environments while also having attributes like adaptability, self-optimisation, self-diagnosis, and self-maintenance (Wang *et al.,* 2019). The study of intelligent systems also looks at how these systems relate to people in dynamic, ever-changing social and physical settings. Early robots lacked autonomy in their formative stages and were unable to make choices. They pretended that the universe was predictable and constantly took the same actions in the same circumstances. A robot viewed today as an autonomous system, can detect its environment and operate in the real world to accomplish a goal. Artificial intelligence, automation, machine learning, intelligent materials, intelligent sensing systems, and programmed self-assembly are examples of such advancements. Intelligent system advancements are fundamentally changing our civilization and will have a profound impact on the future (Schwab & Zech, 2019; Xing & Marwala, 2017).

In HEIs, the application of intelligent systems occurs in a variety of ways. These include choosing which students to admit and choosing their courses; early warning systems for first-year at-risk students; intelligent tutoring systems; imparting course material; and identifying students' strengths and limitations. Other uses include selecting instructional materials based on student needs; promoting student collaboration; assessing and evaluating students' understanding, engagement, and academic integrity; evaluating teaching; using adaptive systems and personalizing course content; assisting academics in learning and teaching design; and using academic data to track and direct students' progress (Zawacki-Richer *et al.*, 2019). Intelligent systems are transforming the way higher education institutions manage and deliver ICT. These systems utilise algorithms and techniques in machine learning to analyse volumes of data, recognise recurring patterns and provide valuable insights that can guide decision-making processes and enhance the quality of services.

2.9 Decision Support Systems (DSS)

The creation of the first Decision Support Systems (DSS) occurred in 1971. However, today they enable decision-makers to use data and models to tackle unstructured problems. Accordingly, Gorry and Scott-Morton (1989) noted that management support systems underwent re-organisation as they transitioned from the utilisation of an information system designed exclusively to facilitate the decision-making process. Gorry and Scott-Morton (1989), went on to define management support systems as "an interactive computer-based system." However, as time progressed the idea of a management support system transformed into the concept of DSS. A DSS is the most well-organised instrument available today for dealing with any situation for quick and resolute judgments (Ghazali & Suhaimi, 2023). All secretarial organisations, especially those in the field of education, are responsible for making decisions. All school managers have a major responsibility that involves making decisions. The act of gathering and evaluating relevant information regarding administrative situations to choose the best course of action from a variety of options characterises decision-making, which is a fundamental managerial responsibility. Managers at HEIs must have a good understanding of the making of decisions. This is because the educational sector, like all regulated businesses, is mostly a structure for making decisions (Fakeeh, 2015).

Different stakeholders' and experts' perspectives on the conceptual characteristics of decision support systems exist (Khodashahri & Sarabi, 2013). A DSS is a computer-based information system that assists in making decisions for businesses or organisations. A DSS is any instrument used to speed up the decision-making process in complex systems, typically when information is ambiguous or incomplete (Michael, 2005). Computer information systems that provide managers and employees with active information support during decision-making are known as decision support systems (Ebrine & Marakas, 2010). A subset of information management systems called DSSs aid managers, planners, and analysts in the decision-making process Clohessy and Acton (2019); and Gao et al.(2021) state that a decision support system is a computer-based tool that helps decision makers tackle structured problems by utilising data and quantitative models. These systems might offer a unique decision-making paradigm and decision-making status. Figure 2.4 below shows a schematic view of DSS.

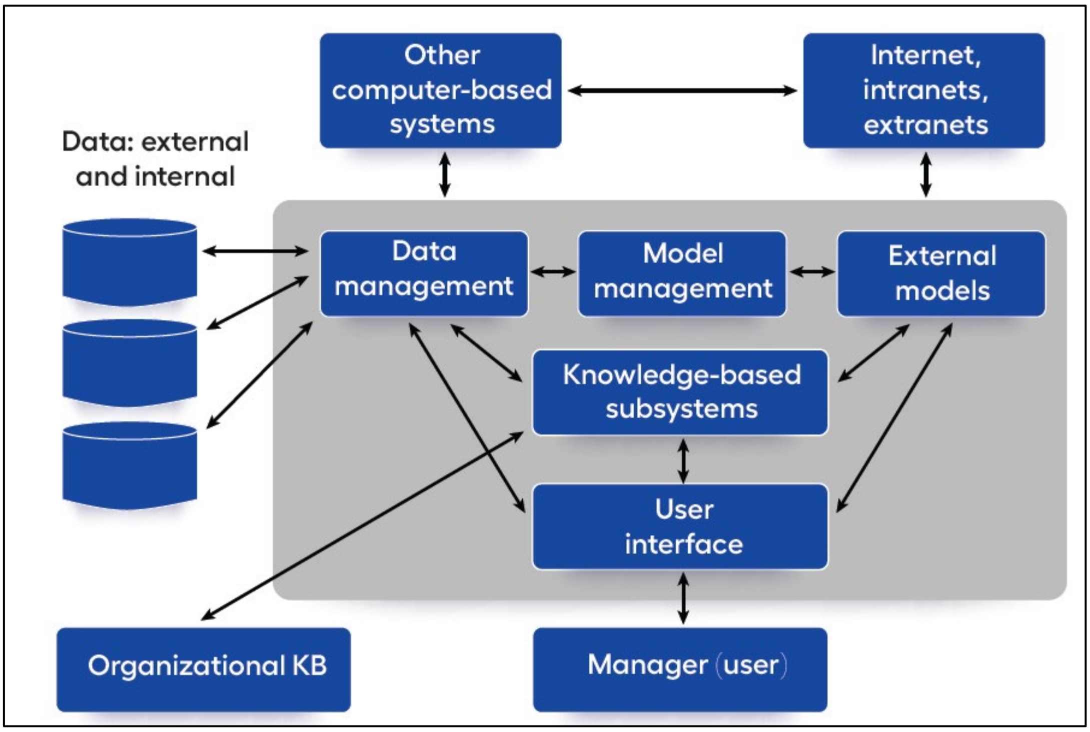


Figure 2.4 Decision Support System Schematic View (Aronson *et al.*, 2005).

The primary characteristic of DSS is their focus on the computer's ability to aid decision-making by introducing problems and improving comprehension of the decision-making context through access to data and model-based decision-making that is appropriate (Fadainejad & Sadeghi, 2011). DSSs play a role in assisting levels of an organisation such as management, operations and planning in making decisions that can dynamically change and are difficult to anticipate in advance. These systems also incorporate components based on knowledge within their framework as emphasised by Rajni (2016). The design of these methods assists mid-level and senior managers in making those tough decisions for unidentified parameters (Sodiya *et al.*, 2012). DSS systems employ a variety of techniques, each of which contributes to the process in a unique way. Following that, a DSS makes judgments using algorithms generated from knowledge of the application area. In response to the growing competition in innovative training environments, HEIs are trying to implement frameworks and make innovative tools. The benefits of using decision support in IT services are numerous (Friedman & Carmeli, 2018; Feng et al., 2022). First, it can help institutions to optimise their operations and reduce costs by automating manual and repetitive tasks, freeing up staff time for more strategic and value-added activities. Second, it can improve service quality by providing faster, more accurate, and personalized support to users. Third, it can enhance decision-making by providing data-driven insights and recommendations that can inform policy and process improvements.

2.9.1 Features of Decision Support Systems

In line with the aim of this study to develop an AI-enabled decision support system for South African Higher Education Institutions. Jia et al (2022) outlines the key traits of DSS. These traits include the system's capacity to manage substantial amounts of data, conducting searches in databases. Additionally, DSS can gather and process information from various sources, including external data from mainframe systems and networks. It exhibits flexibility in generating tailored reports and presentations, accommodating the specific requirements of decision-makers. DSS incorporates graphical elements such as tables, charts, and trend lines for effective data visualisation. Furthermore, it leverages software programs to perform analyses and comparisons. DSS supports decision-makers through heuristic, optimisation, and satisfying approaches, providing a range of options to address complex situations. Lastly, it conducts hypothetical, goal-oriented analyses, enhancing its utility in aiding decision-making processes.

2.9.2 Decision Support System Capabilities

DSS strives to provide the knowledge required to assist humans involved in the decision-making process in getting over the obstacles they face. South African HEIs could rely on legacy systems, which have advantages and disadvantages. Since they have been in use for so long, they are dependable. Systems' drawbacks include their inability to scale or work with the most recent enterprise resource planning systems and other innovative technologies like ML, AI, or robotics (ITG Institute, 2008). HEIs make decisions based on historical data kept in their archives, but systems operate in isolation and house this data. Reports made from historical data are notable examples of descriptive analytics, such as statistics on past performance.

According to Tripathi (2011), DSS exhibits a range of capabilities. Firstly, they assist in all phases of problem-solving, including insight, design, decision-making, execution, and monitoring. Secondly, DSS can support decision-making across various frequencies, whether it is dealing with major events like company mergers or routine tasks like weekly inventory management. Additionally, the tailoring of DSS achieves unique judgments through ad hoc systems or manages repetitive decisions with institutional DSS. Furthermore, DSS is versatile in addressing different issue formats, spanning from unstructured and non-programmed scenarios to structured and programmed ones. Lastly, DSS accommodates decision-making at various levels, including tactical, operational, and strategic decision levels, making it a versatile tool for organisations. The previous DSS report is crucial to this analysis because it gathers system information (one database). Management mines data analyses, interprets, and makes decisions using AI and ML (Mahrinasari *et al.,* 2021). This calls for complicated processes not included in traditional DSS, such as decision support systems that assist in future prediction. There are modern technologies available that help predict future trends and changes that will affect the institution or organisation. This is useful because knowing what happened in the past is not especially useful if such data cannot be unusable to predict future trends and events (Schwab & Zech, 2019). Predictive analytics is a method employed in another type of DSS that calculates the likelihood of events happening by utilising a blend of data mining, statistical tools and machine learning algorithms. Banks, for instance, employ AI and ML decision support systems to find fraud. HEIs might embrace and use these techniques for decision-making, as insurance firms do.

2.9.3 The Importance of Decision Support Systems

Shah (2014) highlights several advantages of utilising DSS. Firstly, DSS can contribute to improved interpersonal relationships by providing decision-makers with informed choices, thereby reducing the likelihood of conflicts arising among them. Secondly, DSS facilitates the automation of administrative processes, streamlining operations and saving time. Additionally, it boosts decision-makers' confidence by reducing frustration and aiding in more effective decision-making. Moreover, DSS can offer suggestions for innovative strategies and provide access to fresh data, enhancing an organisation's ability to adapt and innovate. Furthermore, DSS supports efficient time management, as quick decision-making can significantly impact a business (Jia et al., 2022). Therefore, the integration of DSS into an organisation can lead to increased effectiveness and productivity. Considering these benefits, incorporating Artificial Intelligence (AI) into DSS can further enhance these advantages by harnessing AI's capabilities for data analysis, pattern recognition and predictive insights, thereby elevating decision-making processes to a more advanced and efficient level which is the objective of this study.

2.10 Role of DSS in Higher Education Institutions

Across the world, people recognise the importance of education for society and for developing the mind. The intense competition and escalating demand for better services have significantly raised the workload, labour needs, and operating costs for HEIs. Although some aspects are specific to academia, HEIs face similar demands as businesses do to improve the quality of their operations and management. Therefore, HEIs should make an effort to use more of the data they gather, invest more money in tools that allow them to directly gather and manage information, as well as adopting participatory based decisions where all valuable stakeholders such as students, the teaching community and the host community would be integrated with the decision-making process (Bresfelean & Ghisoiu, 2009).

Agbo and Ogai (2013) assert that the main purpose of DSS is to transform data from sources into information that assists in making informed decisions. Management and business contexts apply DSS technology extensively, where executive dashboards and other corporate performance technologies play a role in expediting decision-making processes, identifying concerning patterns and improving resource management efficiency. DSS allows all information from any organisation to be summarised in the form of charts, graphs, and other visual representations, which aids in the strategic decision-making of the HEI management. Making the right choice is crucial because it can determine the institution's success or failure. For this reason, it is crucial to make timely and highly effective decisions. Manual data collection and analysis is a time-consuming and ineffective process, especially when there is intense competition. In this situation, DSS played a part in developing the mechanisms that enable educational managers and stakeholders to make better and quicker decisions (Shalabi, 2020). According to scholars like Anwar and Ashraf (2014), one of the factors influencing the adoption of DSS in the educational sector is the success rate achieved with its application in other commercial sectors. In particular, the researchers pointed out that schools, colleges, and institutions all around the world do not extensively use DSS tools.

2.11 Benefits of DSS in Higher Education Institutions

Higher education institutions gather data that has analysis possibilities (by aggregating and analysing it effectively). Under these conditions, the ICT department requires decision-supporting tools that might provide extremely accurate information and facilitate all managerial procedures (Bresfelean & Ghisoiu, 2009). Even though the success of the application is known in the business world, their use in HEIs is still relatively new. In recent years, HEIs have been facing significant pressure to improve their IT services and keep up with the fast-changing technology landscape. With the growing reliance on digital technologies in teaching, learning, research and administrative operations, IT services have become critical to the success of these institutions. However, providing efficient and effective IT services can be a challenge, especially in the face of budget constraints and resource limitations.

One of the problems this study is attempting to address is that the case university currently utilises information systems that function independently. There is a lack of cohesion. The information systems produce a volume of data, however, processing this data can be challenging due to its complexity. Agbo and Ogai (2013), state that DSS provide a framework for solving problems that are semi-structured and unstructured and that DSS provide HEIs with important benefits in the following ways:

- Increased personal efficiency.
- Expedited decision-making processes.
- Enhanced organisational control.
- Improved problem-solving processes within an organisation.
- Facilitated good workplace interpersonal communication.
- Encouraged employees' continuous learning and training.
- Acquired competitive edge over its competitors.
- Identified and novel ways of approaching the problem area.
- Afforded automation of managerial procedures.
- Generated ideas to boost performance.
- Simplified value-chain activities.
- Encouraged decision-making regarding experimentation with learning of new things.

2.12 The concept of Artificial Intelligence

Understanding the concept of AI and how it works is extremely important. This knowledge forms the basis for the research study, which aims to develop a decision support system that incorporates AI capabilities. The goal is to provide the ICT department of the case university with a toolset that can turn data into insights. To achieve this, it is important to understand what AI can do and explore its foundations. By doing so we can lay the foundation for a solution that has the potential to revolutionise decision making in the ICT department of our university. This will improve efficiency and adaptability in our changing technological environment. According to Pavel and Johanne (2017), artificial intelligence is a subfield of engineering that develops and uses original ideas and techniques to address difficult problems. In addition, Sarmah (2019) defined AI as a field within computer science that focuses on exploring ways in which machines can replicate intelligence. There is a view that computers may one-day rival human intelligence as processing power, memory, and software continue to improve. AI has become an increasingly popular and influential field of study in recent years. AI refers to the creation of computer systems for conducting tasks that would typically necessitate intelligence such as recognising speech, making decisions and solving problems (Mahrinasari *et al.,* 2021). The progress of AI has caught everyone by surprise. In the last few years, incredible strides have occurred in the quest to put AI ideas through their pace.

The development of AI has led to natural applications, such as autonomous vehicles, Big Data, and medical research. Designers of AI systems try to create systems that are as intuitive and creative as humans. Chatbots work with multiple levels to show how AI can speed calculations and automation, while virtual assistants that help people think and learn show how it can apply in real life (Chatterjee, 2020). As per Figure 2.5 below, there are several key components of AI that are essential for creating intelligent systems. These elements consist of machine learning, processing of language, visual comprehension by computers and robotics. Each of these components plays a critical role in enabling AI systems to learn from data, understand and interpret human language, recognise patterns in images and video, and interact with the physical world through robotics. In this context, understanding the key components of AI is essential for developing advanced AI systems and applications that can help solve complex problems and improve our lives.

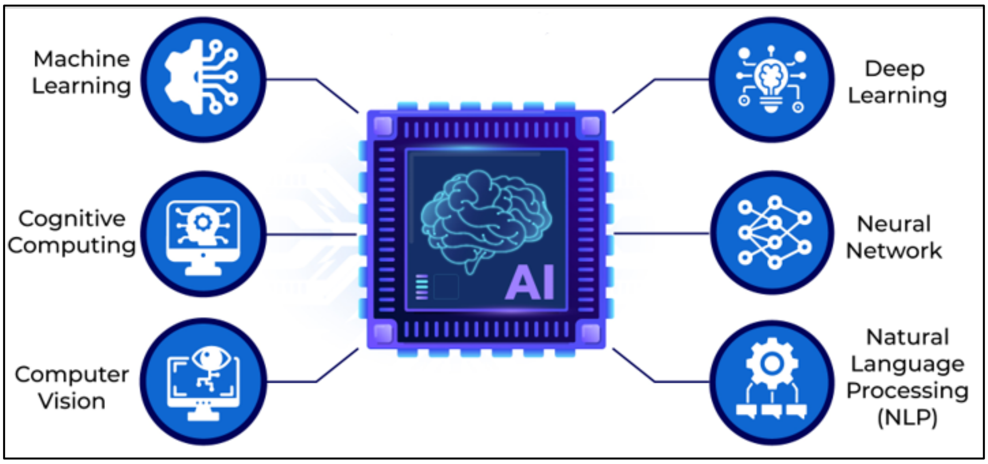


Figure 2.5 Key Components of Artificial Intelligence (Kanade, 2022)

Machine learning: According to Poole and Mackworth (2010) machine learning models human learning by collecting and analysing substantial amounts of data to make predictions. Machine Learning (ML) is a class of algorithms that help programs make better predictions about user behaviour. No explicit programming occurs in the process. Saracco (2018) established that the main objective of ML is to develop algorithms that can receive data, analyse it from a perspective and subsequently generate a prediction or an updated prediction when provided with input data.

Deep Learning: The deep learning feature of AI simulates the way the human brain works to discover and use patterns for processing data and making decisions. To manage AI's ability to learn from unstructured or networked data, researchers have developed a technique called deep learning. Using deep learning, neural networks help the processing of data leading to resultant predictions. Russel, Daniel and Max (2015) visualise a network-based structure linking a network to the human brain.

Cognitive Computing: The term "cognitive computing" describes the evolution of AI that mimics the human brain in differing ways, including its capacity to comprehend natural language, learn from experience, naturally interact with humans, and assist with decision-making (Kelly and Hamm, 2013). Learning systems are at the heart of any cognitive computing system. They include data-centric architectures, which bring storage, memory, switching and processing closer to the data, as well as embedded data analytics and automated management. They use a method that is neither linear nor deterministic to process huge data sets.

Kelly and Hamm (2013) state that the most unique things about cognitive computing systems are that they are:

- ***Information Adept***: this connotes the ability to integrate enormous amounts of data from various disparate sources and generate novel insights or solutions regarded as information adeptness.
- ***Adaptive***: their ability to dynamically evolve in time as they encounter new data, analytics, users, interactions, research, or work environments.
- ***Probabilistic***: this entails discovering contextually relevant patterns, statistically creating and identifying patterns in context using analysis to generate and assess hypotheses based on evidence and predicting the probability of valuable connections. Providing solutions based on learning and deep inference are all examples of the probabilistic approach. One aspect of this is the discovery of unforeseen patterns by mechanical means.
- ***Highly Integrated***: The modules work together in a manner with each module influencing the learning system. Data, interactions and the previous data of modules are constantly influential. Automatic oversight of the workload occurs.

- ***Meaning-Based***: operate based on meaning utilising natural language processing and integrated analytics to maximise the potential of the structure, meaning and connections of language.
- ***Highly Interactive***: focus on interactivity: This involves combining human computer interactions, data analysis, visualizations and providing tools and designs that facilitate communication, within the integrated system.

Neural Network: To enhance machine learning, showcase knowledge and optimise the outcomes of systems, novel systems and computational techniques called artificial neural networks (ANNs) or neural networks have emerged as powerful instruments. (Chen *et al.,* 2019). An ANN is a data processing model inspired by the structure and function of biological nerve systems like the brain. Many professionals in the field of artificial intelligence view networks as the most promising and perhaps the sole solution for developing a computer with true intelligence. Networks of artificial neurons mimic the structure of the human brain by simulating the interconnections between neurons. Human brain is composed of a vast number of neurons, estimated to be in the billions. A neuron's cell body is responsible for transporting information into and out of the brain (inputs and outputs) (Van Gerven & Bohte 2017). The primary concept behind these networks is (loosely) derived from the functioning of the biological brain system, which is to analyse data and information to learn and develop new knowledge. The primary concept here is the development of alternative data-processing architectures.

It is becoming increasingly common to employ artificial neural networks for controlling or modelling systems whose fundamental architecture is either unknown or extremely complicated. When a neural network regulates the input of a machine, for instance, the network itself learns how to regulate the machine's operation. Adaptive learning occurs in these systems when newly introduced inputs cause the system to create the appropriate response by altering the weight of the synapses according to the given data (Wu & Feng 2018). During the training of a neural network, it receives a series of inputs and the results of those inputs (using one of the training methods). Two common types of ANN architectures are feed-forward and feedback. A unit in a feed-forward system delivers data to another unit but receives no feedback in return. According to Dastres and Soori (2021), each node receives input data from its left-most nodes, multiplied thereafter by the connection weight. This provides output results that are related to the importance of each connection. The technique has potential uses, including pattern formation, identification, and categorization. The desired outcome of the network is known in advance, leading to system implementation (Al-Zewairi, Almajali, and Awajan 2017). Based on this idea, entrepreneurs build successful businesses with computer vision being one of the well-known focal points.

Computer Vision: To make computers see and grasp the content of digital images and videos is the goal of computer vision research. Simply described, it is the branch of science that teaches computers to recognise and comprehend images of the physical world. This is because computer vision systems use AI and deep learning models to interpret the digital images they take and act accordingly. It is interdisciplinary, with roots in AI and ML, and its methodologies and algorithms rely on both. Computer vision aims to decipher depicted content of digital images. This typically entails elicitation of emergent strategies that aim to mimic humans (Lawaniya, 2020).

According to Jähne (2000), the following are all necessary parts of a computer vision system:

- ***Radiation Generator***: If there is no radiation emission by the scene or the object of interest then no processing occurs. Accordingly, things that are not glowing need to have the right kind of lighting applied to them.
- ***Camera***: the “camera” collects radiation received from the item to allow the identification of radiation's source. The most straightforward explanation is that it is simply a lens. It may be something altogether different, like an x-ray tomograph, a microwave dish, or an imaging optical spectrometer.
- ***Sensor***: Upon receiving a certain radiative flux density, the sensor processes it by transforming it into a usable signal. Typically, when capturing the distribution of radiation an imaging system relies on a 2 D array of sensors. However, in cases a single sensor or a row of sensors can suffice if a scanning system is employed.
- ***The computing core***: to classify and quantify object qualities, it analyses the incoming, typically higher-dimensional data and extracts relevant features. Another crucial part of the system is a memory system that can retain information about the scene as well as procedures to get rid of irrelevant data.
- ***Actors***: observational results prompt responses from the actors. When the vision system is actively engaged in processing information such as when observing an object of interest or navigating using cues it plays a crucial role within the overall vision system (referred to as active vision or the perception action cycle).

The primary difficulty in computer vision is object recognition. Currently, only large, solid objects, such as faces, are easily identified. In other contexts, though, object detection remains a challenge. Deformation, appearance variation, scale variation, blurriness, are just some of the difficulties that must be overcome. Object detection is not the only pattern recognition problem with no clear solution. Everyday life is aided by computer vision since it enables us to learn more about any static digital image or video. Object detection can also be practically implemented with the help of the Python programming language and several available modules and packages. Lawaniya (2020) reports that tensorflow, the OpenCV module (for real-time image and video captioning), and the You Only Look Once (YOLO) library are a few examples of helpful resources.

Natural Language Processing: With the help of NLP, computers can now have conversations with humans in their native tongue and scale up a variety of other language-related jobs. For instance, NLP empowers computers to understand written text and comprehend language, analyse it, quantify thoughts and emotions, and prioritise its components. Saleh (2019) argues that now more than ever, computers can perform linguistic analyses that people cannot keep up with, and they can do it in a continuous, objective manner without getting tired.

2.12.1 The Typology of Artificial Intelligence

The following list groups artificial intelligence as:

- Artificial Narrow Intelligence (ANI).
- Intelligence simulations (AGI).
- Artificial Super Intelligence (ASI).

Artificial Narrow Intelligence (ANI): ANI solutions, also known as machine learning, focus exclusively on a single-issue domain. Artificial intelligence of this type is currently available on the market, and it can perform common functions such as making product recommendations and making accurate weather forecasts. Sources may disagree with this, but it is undeniable that ANI is the only type of commercialised AI, existing in a meaningful way (Sarmah, 2019).

Intelligence Simulations (AGI): The next step up from ANI is Artificial general intelligence (AGI) aims to exhibit abilities to humans. To replicate behaviour effectively an AGI system would need numerous ANI systems interconnected. To put it into perspective IBM Watson, a leading system in the industry took 40 minutes to imitate one second of neuro activity. Li and Du (2017) contend that the ongoing endeavours of corporations in developing AGI are. We will eventually achieve success.

Artificial Super Intelligence (ASI): Here is where the imagination begins to wander into the realm of science fiction. Artificial superintelligence (ASI) refers to a system that can easily outperform any form of human intelligence. It has the capacity for original thought, logical decision-making, the establishment of meaningful bonds, and the free will to choose between good and evil. An assumption exists that the jump from AGI to ASI is not large. A super-intelligent system would be the natural progression of AGI once machines can generate their ideas (Pannu, 2015).

2.12.2 AI versus traditional information systems

AI materialises when a machine can perceive, reason, learn, interact with its surroundings, and solve problems creatively (McKinsey, 2018). Purely software-based AI systems exist and can include things like the voice assistants and image/face recognition apps we use on our smartphones and in the cloud (Press, 2017). Hardware technologies, such as self-driving cars or drones, can also incorporate AI.

In contrast to traditional information systems, which encompass a wide range of functions from brochures to search engines and databases, most existing IT infrastructures serve specific, siloed purposes, often hindering the seamless sharing of data across various sources. This fragmentation can pose challenges for managers in accessing relevant information necessary for effective decision-making (Calero, Moraga & Piattini, 2008). Artificial intelligence, however, sets itself apart by its ability to learn from vast and diverse datasets spanning various formats and time periods. Unlike traditional information systems that require pre-programmed instructions for data processing, AI systems possess the capability to organically develop their data analysis approaches as they assimilate and analyse incoming data (Kellogg *et al.*, 2020). Consequently, AI-powered software can excel in modeling complex decision problems and offering valuable recommendations to optimise outcomes (Dietvorst *et al.*, 2015). Despite concerns regarding algorithmic opacity, which can render machine learning (ML) algorithms invisible and potentially raise scepticism about results (Fomin, 2020), AI proponents like Lyytinen, King, and Nickerson (2018) advocate for the incorporation of a model that allows for comparisons to ensure consistency. This approach contrasts with the traditional computing paradigm, where verification against the computational model's algorithm is straightforward.

By leveraging AI tools, higher education institutions can overcome the limitations of traditional information systems and stay ahead of the curve (Manhiça *et al.*, 2022). AI's capacity to process and analyse diverse data sources, offer insights, and provide decision support empowers these institutions to provide world-class IT services that drive innovation, efficiency, and excellence in both academic and administrative realms. Systems rely on strict control and have little tolerance for deviations in logic and output. However, the programming of such instructions does not relate to the machine learning algorithms that drive AI. On the contrary, the provision of datasets comprising information on focused computation needs and the correct outcomes of the computation, constitutes the machine learning system. In IT systems "input data" and "output data" refer to datasets. Later, the ML system attempts to deduce, given the input, how to arrive at the desired output. The system "learns" from this "trying," so to speak. Traditional computing systems programmed with fixed, codified human knowledge, never learn (Lyytinen, King, & Nickerson, 2018), making AI's primary attribute of learning an essential contrast. The ability to learn new things quickly is crucial to artificial intelligence, but it also makes it more susceptible to bias than older forms of information technology.

2.12.3 Artificial Intelligence Applications in Higher Education Institutions

Chatterjee & Bhattacharjee (2020) stipulate that the decline in the quality of higher education in low- and middle-income nations is commonly attributed to differing factors. These encompass challenges such as limited institutional independence, inflexible educational frameworks, ineffective affiliation and disposal processes, as well as inadequate financial support from both public and private sources. Therefore, low and middle-income nations urgently require a change in thinking to improve the quality of higher education delivery and the teaching-learning environment (Menon *et al.,* 2014). Aspects of higher education could use a facelift (Silander & Stigmar 2019). Thus, Croxford and Raffe (2015) contend that most low- and middle-income countries have an immediate need to include innovative technologies like artificial intelligence in their higher education institutions.

Significant changes have already occurred in the HEI sector because of the introduction of such technologies, which have supplied students with new abilities with far-reaching repercussions (Asthana, & Hazela, 2020; Liu, *et al.*, 2018). There is a wide variety of pattern usage where HEIs could use artificial intelligence by making use of innovative tools and massive amounts of data. Therefore, Calegari *et al.,* (2020) argue that the improvement of deep learning and neural networks supports the use of Big Data for forecasting and making autonomous judgments. Most modern intelligent systems make use of machine learning. NLP is another significant element of an intelligent system, enabling the mining of a wide range of scientific databases. Bavakutty, Salih, and Mohammed (2006) say that the search for information becomes easier and more productive when information needs relate to natural language at every stage of the retrieval process.

When promoted properly, the use of data analytics and artificial intelligence in HEIs can help secure the institution's success (Saif et al., 2022). HEIs have developed chatbots to interact with students on a personal level, sift through applicant data, and then use that information to construct digital teaching assistants. Industry pioneers in education and technology are currently employing AI to alleviate mundane, repetitive work and provide a more interesting and effective experience. As time goes on, the rest of them will catch up with them. As soon as that happens, institutions and colleges can automate their routine tasks with the help of AI and ML (Kuleto *et al.,* 2021). For this reason, by leveraging AI tools, higher education institutions can stay ahead of the curve and provide world-class IT services that drive innovation, efficiency, and excellence.

In recent years, the world's top HEIs have come to recognise that AI and ML are integral to the future of learning and global progress. There is growing empirical evidence of AI's use in higher education institutions, particularly in countries with high incomes and advanced technology infrastructures like the United States. According to Chang (2017), 65% of American colleges support AI and ML. Deakin University, located in Australia utilises IBM Watson to address student queries while the University of Derby, in the United Kingdom has implemented a system that analyses data to anticipate when students may withdraw from their studies and offers interventions. These examples highlight how education institutions embrace artificial intelligence (Lacity, *et al.,* 2017). To add to this, Kumar (2021) discovered that AI and ML are playing a role in enhancing the safety and productivity of HEIs. They provide a flexible and easily accessible computing environment for students to conduct research and develop their skills. An analysis by McKinsey (2017) found that teachers put in an average of 50 hours per week, but teaching occupies only about twenty-five of those hours. Twenty per cent to forty per cent of a teacher's time concerns tasks that could be mechanised with today's technology, according to forecasts. Utilisation of AI and ML to aid students is on the rise in the academic world. Students benefit from the use of machine learning in the classroom. Some useful apps can help students organise their schedules in an automated fashion. AI can improve higher education institutions. By analysing a user's past actions and recommending improvements, AI and ML may personalize the user experience automatically.

2.12.4 Artificial Intelligence Application in South African Higher Education Institutions for Decision Support Systems

Implementing decision support systems effectively to sufficiently inform the choice process is essential to any organisation's success, but so are less tangible qualities like imagination and creativity (Shamsan *et al.,* 2022). Given the increasing global competition and the increased unpredictability brought on by exposure to a greater number of competitors, the capacity of HEI to make sound decisions is more crucial than ever (Shamsan *et al.,* 2022). The process of making decisions in a HEI or any other type of organisation needs careful thought and management (Shimizu, de Carvalho, & Laurindo, 2005). Knowledge management strategies can adjust to improve HEI efficiency and to evaluate and manoeuvre ICT in effective ways if educational administrators and managers have adequate background knowledge about the organisational cultures relevant to their roles and how they relate to knowledge transfer (Kuleto *et al.,* 2021). Computers, with their ability to collect and analyse vast volumes of data (known as "Big Data") in accordance with predetermined rules and procedures, can make choices predicated on empirical evidence and theoretical models (Teng *et al.*, 2023). When making decisions, AI-based systems do not have the biases of humans and give a more accurate picture of the world (Dymond *et al.*, 2010). According to Dejoux and Léon (2018), with the use of ML and algorithms, AI can make decisions on its own. Machines are already deciding whether to do high-frequency trading. Data and digital services have long played a key role in the South African educational system. Intelligent tutoring systems are a popular use case for AI in the classroom.

Most systems like intelligent tutoring systems also use data or learning analytics for monitoring progress and habits. An intelligent tutoring system can identify a student's preferred learning style and approach by compiling data about them and analysing it with machine learning methods (Mlambo-Ngcuka, 2013). Automating tests with AI-powered systems can help academics better understand their students' cognitive capacities and spot any potential learning challenges, all while decreasing their administrative workloads. In principle, this frees up classroom time for academics to focus on encouraging creative problem-solving (Ilkka, 2018). In ICT, AI can, amongst other things, automate routine tasks such as password resets, user onboarding, and software updates, reducing the workload for IT staff and enabling them to focus on more complex tasks. Enabling the ICT department with AI involves moving from traditional decision-making methods that heavily depend on intuition or past experiences and embracing a more data driven and analytical approach (Teng *et al.*, 2023). By leveraging AI, the decision support system can play a role in enhancing the department’s decision-making process by considering variables and scenarios enabling them to tackle dynamic challenges.

2.12.5 AI Decision Support System Challenges in South African Higher Education Institutions

There is minimal information about the usefulness of AI in HEIs globally, and there are pressing problems about the relative cost-efficiency of established technology, such as individual tablets, in the South African environment (Roberts & Vänskä, 2011).

In a review of studies conducted between 2007 and 2018, by Zawacki-Richter *et al.* (2019), on the topic of artificial intelligence in higher education sector, noted that:

- Several papers provided a critical overview of AI in education.
- A selection of studies has also explored the connection between teaching methods and data driven systems.
- A few papers reflected concerns about the implications of utilising data and AI in educational settings.

Artificial intelligence-enabled decision support systems have the potential to revolutionise decision-making processes in industries, including South African higher education institutions (Chilunjika *et al.,* 2022). These systems can help institutions make data-driven decisions that are more accurate, efficient, and effective. However, implementing AI-enabled decision support systems in higher education institutions in South Africa comes with its own unique set of challenges. Challenges posed by an artificial intelligence-enabled decision support system include concerns about ethics and privacy problems related to the quality of data and the requirement for skilled personnel to manage and interpret the outcomes. As part of this study the researcher will continuously evaluate the benefits and risks of using AI decision support in IT services and develop appropriate strategies and policies to ensure responsible and effective use. Addressing these challenges will require collaboration between technical experts, institutional leaders, and stakeholders to ensure the effective development, implementation and maintenance of AI systems. By doing so, higher education institutions in South Africa can leverage the power of AI to make data-driven decisions to enhance IT services.

2.12.6 AI for IT Operations

The findings of this study have substantial implications for institutions of higher education and other organisations seeking to effectively implement AIDSS. It is therefore imperative that we explore current attempts of AI in IT operations (AIOPS). Li *et al.*, (2020) describe AIOPS as solutions that utilise machine learning (ML) methodologies and operational data to facilitate diverse objectives in software and system operations. According to Bhardwaj and Sabharwal (2022), AIOPS encompasses the integration of machine learning, Big Data analytics, and advanced artificial intelligence techniques to enhance and simplify aspects of IT operations. These aspects include monitoring, incident response, and performance optimisation. AIOPS transform the processes of automation, monitoring, and service desk tasks. The implementation of this approach results in a reduction in network downtime, an improvement in overall system availability, and an enhanced level of customer satisfaction (Lin *et al.*, 2018).

By alleviating the ICT department of routine daily tasks, it enables them to allocate more time towards long-term projects. AIOPS serves as a vigilant companion that monitors systems and proactively notifies users of potential issues prior to their escalation into critical states. Gartner (2018) projected that by 2022, 40% of global enterprises will have strategically implemented AIOPS solutions to support their IT operations. The utilisation of AIOPS is enabling businesses to achieve heightened levels of automation, thereby facilitating the streamlining of processes with reduced reliance on human intervention. AIOPS systems possess the capability to analyse extensive quantities of data and extract valuable insights through the utilisation of artificial intelligence and machine learning techniques. According to a recent analysis conducted by Gartner (2023) the utilisation of AIOPS platforms facilitates the automation of routine processes such as incident management, system provisioning, and change management. As depicted in Figure 2.6 a solid comprehension of AIOPS components is vital for the effective and smooth assimilation of Artificial Intelligence into the case ICT department.

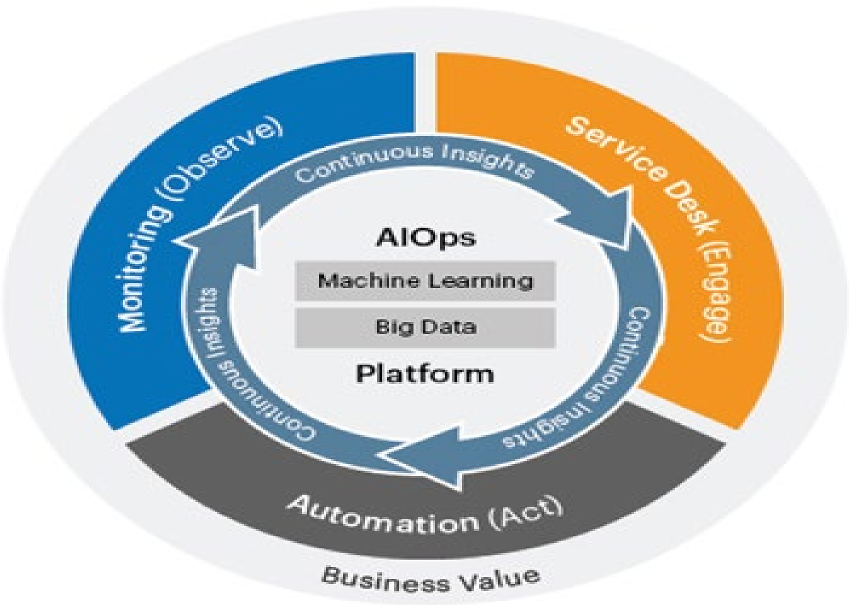


Figure 2.6 Artificial Intelligence for IT Operations (Claridge, 2023)

HEIs encounter a multitude of IT challenges, encompassing the management of extensive datasets, the upkeep of networks, and the administration of diverse applications. AIOps and AI-enabled decision support systems both utilise artificial intelligence to improve organisational decision-making and operational efficiency. AIOPS concentrates on automating IT operations via data-driven insights, predictive analytics, and real-time monitoring to detect and resolve anomalies. Similarly, AIDSS processes data, provides recommendations, and assists decision-makers by utilising AI. Both systems seek to augment human decision-making, learn continuously from data, and progress over time. Integrating AIOPS insights into AIDSS can produce a comprehensive ecosystem for decision support that optimises efficiency and quality in the ICT department.

2.13 Chapter Summary

This chapter provided an overview of decision-making structure and decision support systems in HEIs. It then considers operational decision-making, including overview of processes and benefits. Operational decision-making within the ICT department at the case university is a crucial aspect of ensuring the smooth functioning of the university's information technology systems. The ICT department provides a wide range of services, such as network infrastructure, software and hardware support, cybersecurity, and data management. To deliver these services effectively, the department must make operational decisions daily. These decisions range from routine tasks such as software updates to major decisions such as implementing modern technology solutions. One of the key challenges faced by the ICT department is balancing their budgetary constraints with the need to provide effective IT services to the university community. This requires careful planning and evaluation of options to ensure that resources are allocated efficiently and effectively. The ICT department must consider factors such as the cost of implementing and maintaining technology solutions, the potential impact on productivity and efficiency, and the needs of different stakeholders within the university community. Collaboration with stakeholders is also essential for effective operational decision-making within the ICT department. By taking this approach they can make sure that their decisions are relevant and effective, improving the overall experience of students and staff. The issue stems from the lack of a system that can efficiently combine the amount of data, different variables and results to assist in making well informed decisions within the ICT department. This shortfall negatively impacts the department’s efficiency, effectiveness and its capacity to adjust to evolving situations. In summary, operational decision-making within the ICT department at the university is a complex and multifaceted process that requires careful planning, evaluation of options, collaboration with stakeholders, and continuous monitoring and adjustment.

In the following chapter, we analysed the research design, methods and tools used. This encompassed methodology, data collection, analysis, ethics, research paradigm, and design. The study followed Design Science Research and Pragmatism, employing a mixed-method approach that provided a holistic understanding, ensuring research validity and reliability. This approach contributed to an innovative AI solution for the university.

CHAPTER 3: RESEARCH APPROACH AND METHODOLOGY

3.1 Introduction

This chapter's discussion will thoroughly analyse the research design, methods and instruments that were used. It highlights how opportunities and challenges posed by the research were utilised productively. Included in the section is the study's methodology, its methods for collecting data, analysis, ethical considerations, research paradigm, philosophical presumptions, its research design and conclusion. Saunders *et al.*, (2018) maintain that the key focuses of a research design are the outcomes, the criteria for the data collection and the analysis. Mohajan (2018) explains that the term "methodology" refers to the strategies, techniques, and processes that are implemented during the study process. On the other hand, the methodology can also be seen as the epistemic foundation of an investigation, according to Silverman (2013). Guided by the Design Science Research and Pragmatism philosophy this study employed a mixed-method approach that incorporated qualitative and quantitative research methods to answer the research questions posed, as recommended by Mason (2012). By utilising both methods the study provided a more robust and holistic understanding of the ICT department context and the effectiveness of the AI-enabled decision support artefact. The qualitative component allowed for in-depth exploration and analysis of the users' experiences and perceptions, while the quantitative aspect provided quantifiable data on the artefact's performance and impact. By employing triangulation, the study ensured that the strengths of a mixed-method approach complement and enhance the validity and reliability of the research outcomes. Ultimately, this study contributed to the development of an innovative and adaptive AI solution for the case university.

3.2 Information Systems Research

Using Kuechler and Vaishnavi (2008) framework for Information Systems research, the researcher was able to investigate the effects of Artificial Intelligence on decision support systems. This conceptual framework was utilised to extract information and identify and illustrate challenges and opportunities that may arise while implementing an AIDSS to improve decision-making in the ICT department and team at the university. The conceptual framework encompasses the contextual environment of the research project, encompassing the individuals and technological elements present within the university under investigation. The project requirements are aligned with the university's operational needs, as dictated by its structures, strategies, roles and the characteristics of its workforce within the ICT department.

The problem's relevance lies in the need for efficient decision-making processes in South African higher education institutions, as demonstrated by this study using the ICT department as unit of analysis. By leveraging the Design Science Knowledge Base, this study integrated theories, frameworks, and models from information systems, and artificial intelligence. In developing the artefact, the Design Science Research Process was followed to define the objectives and requirements, specify design principles, and iteratively develop the AI-enabled decision support system prototype. Further information is provided in the rest of this chapter. The principal objective of this study was to develop an AI-enabled decision-support system; therefore, an artefact was produced at the end of the study.

Rigorous evaluation methods, including Goal Question Metric and stakeholder feedback using a questionnaire were employed to assess the artefact's effectiveness, usability and impact. Through the Relevance Cycle, continuous improvements and refinements were made to the artefact, considering the unique context and needs of South African higher education institutions. The study aimed to contribute to the field by providing a novel and practical solution that enhances decision-making processes, empowers ICT personnel, and advances the understanding of AI-enabled decision support systems in the higher education context.

3.3 Research Paradigm

A paradigm is a research culture with a shared set of beliefs, attitudes and assumptions regarding the nature of research and how it should be conducted. This collection of common views, attitudes, and assumptions is held by a researcher community (Tsung, 2016). In the scientific and academic communities, "paradigm" refers to a pattern, structure, framework, or system of ideas, attitudes, and assumptions (Tsung, 2016). In other words, it is a mental and behavioural approach to performing research.

3.3.1 The Positivist Paradigm

The positivist research paradigm is what serves as the basis for the quantitative method. The realist and objectivist ontology as well as the empiricist epistemology of the positivist approach to research necessitates a methodology that's impartial and objective focusing on the measurement of variables and the assessment of hypotheses that contribute to causal explanations (Sarantakos, 2017; Marczyk, *et al.*, 2010). Research that adheres to the positivist paradigm employs experimental methods to evaluate effects, particularly those that are the outcome of societal shifts. The methodologies for collecting data place a strong emphasis on the collection of numerical data to facilitate the quantitative presentation of evidence (Neuman, 2014; Sarantakos, 2015). The replication of observable findings, the application of variable manipulations to study objects, and the utilisation of statistical analysis are the three primary means by which positivist inquiry arrives at the truth (Guba & Lincoln, 1988; Krauss, 2015). As a result, Creswell (2014) stipulates that positivists place a strong focus on the utilisation of methods that are respectable and valid while attempting to describe and explain phenomena.

3.3.2 The Interpretivist Paradigm

According to Guba and Lincoln (1988), the purpose of interpretivism is to get an understanding of the subjective nature of human experience. This approach tries to go "into the thoughts of the research subjects" to comprehend and interpret what those individuals are thinking as well as how they understand the surrounding environment (Morgan, 2017). Every attempt is made to understand the situation from the viewpoint of the subject, rather than that of the observer (Morgan, 2017). Comprehending the person and gaining an understanding of their perspective on the world is a priority. The reality, in the view of interpretivism, is something that is socially constructed (Punch, 2013). The constructivist paradigm is another name for this research approach. In this model, theorising comes after the study; hence, it is rooted in the outcomes of empirical studies. Data are gathered and analysed using this method utilising grounded theory as the theoretical framework (Morgan, 2017). The foundations of qualitative methodology are found in constructionist ontology and interpretivist epistemology. This assumes that the experiences of the participants have significance and that the perceptions of the researcher are the medium via which this meaning is communicated (Prochaska, 2017). Participating in events, conducting interviews with significant individuals, obtaining life histories, developing case studies, and doing research into existing records or cultural artefacts are all examples of how qualitative researchers study the people and interactions of a culture. Furlong (2010) describes the qualitative researcher as interested in obtaining confidential information regarding the research group. Constructivists and interpretivism criticise experimental and quasi-experimental designs. Constructivists believe that reality can only be comprehended as an integrated whole by studying it in its natural habitat (Furlong, 2010).

3.3.3 The Pragmatism Paradigm

The research paradigm of pragmatism is built on the historical contributions of pragmatism (Maxcy, 2013), and it permits a diverse range of methods. Pragmatism research paradigm suggests researchers should utilise the methodological approach that's most efficient in solving the study topic at hand (Frankel Pratt, 2016). Pragmatism was developed in the 1920s and became popular in the 1950s (Teddlie & Tashakkori, 2009). It is typically associated with mixed-methods or multiple-methods research (Biesta, 2010; Creswell & Clark, 2017; Johnson, & Onwuegbuzie, 2004; Maxcy, 2013; Morgan, 2013; Teddlie & Tashakkori, 2009), in which the questions and consequences of the study take precedence over the methods. Nevertheless, mixed-method research is more pragmatic (Creamer, 2019). Pragmatism is linked to diversity in the social and behavioural sciences, according to Creamer (2019), who also shows this connection. This research conducted a design and development of an AI-enabled decision support system for South African higher education institutions. A realistic approach was necessary to overcome the difficulties presented by this study and accomplish the goals outlined in Chapter One. As depicted in Figure 3.1 below, contrary to positivism and interpretivism, pragmatism allows for several research tactics and procedures to be utilised within a single investigation (Saunders *et al.*, 2018).

	RESARCH APPROCH	ONTOLOGY	AXIOLOGY	RESEARCH STRATEGY
Positivism	Deductive	Objective	Value-free	Quantitative
Interpretivism	Inductive	Subjective	Biased	Qualitative
Pragmatism	Deductive / Inductive	Objective / Subjective	Value-free / Biased	Qualitative and / or Qualitative

Figure 3.1 Positivism, interpretivism and epistemologies (adapted from Wilson, 2014)

Pragmatism fundamentally revolves around the concept of "what works," and thus primarily pertains to the pragmatic truth theory. Pragmatism is essentially focused on addressing real-world issues. It operates on the premise that practicality takes precedence over presumptions about the essence of knowledge (Creswell, 2014; Hall, 2013; Shannon-Baker, 2016). In essence, pragmatism guides research methodologies, emphasizing action and practicality (Cameron, 2011).

An interpretivist paradigm was utilised in this study. The study’s aim was to develop an AI-enabled decision support artefact, and it employed a comprehensive research approach that combined subjectivism. The subjectivist perspective was embraced during the early stages of the research process, specifically in problem awareness and the suggestion phase, which followed the design science research process. Subjectivism allowed for a more exploratory and user-centric approach, where the researchers sought to understand the perspectives and experiences of the end-users. This involved gathering qualitative data through interviews to gain insights into the users' needs, preferences and challenges. By combining objectivism and subjectivism, this study ensured a well-rounded and holistic approach to the development of the AI-enabled decision support artefact. The objective evaluation provided measurable and concrete evidence of the artefact's performance and efficiency, while the subjective exploration allowed for a deeper understanding of the users' requirements and enabled the artefact to be tailored to their specific needs. This integrated research approach enhanced the artefact's practicality, usability, and relevance in real-world decision-making scenarios.

3.4 Philosophical Assumptions

Creswell and Poth (2018) emphasised that, “whether we realise it or not, we invariably bring specific perspectives and philosophical assumptions to our research endeavours”. The way a researcher seeks information to address research questions and the criteria used to evaluate a study are both influenced by philosophical assumptions. Hence, these assumptions create the foundation upon which the research process is built. The argument presented by Creswell and Poth (2018) emphasises the significance of being aware of these assumptions since they influence the research process. The initial part of the research process is the development of research questions, followed by the planning of how the issue will be explored, designing the research and choosing appropriate methods for data gathering and analysis. This session provides a comprehensive analysis of ontology, epistemology and axiology.

3.4.1 Epistemology

The study of epistemology delves into the foundations of knowledge as well as its scope (Creswell & Poth, 2018; Slevitch, 2017). It investigates how people learn and remember information. A researcher can justify assertions about their level of understanding and define what it means to be a researcher (Cresswell & Poth, 2018). Moreover, scientists can conduct research on topics they already understand. However, quantitative research presupposes the existence of a neutral, objective, and logically ordered world, regardless of the viewpoints held by researchers and participants (Slevitch, 2017). In terms of epistemology, quantitative research has an etic perspective, which means that researchers are regarded as being on the outside looking in. They are unable to influence or be influenced by the truth that is objectively decided (Creswell & Poth, 2018). Interactions between researchers and participants or the object of study are crucial in qualitative research to achieve a thorough grasp of the topic. In qualitative research, reality is dependent on the mind and is socially produced, hence the only things that can effectively explain it are perceptions and interpretations (Slevitch, 2017). The methodology that a researcher uses to carry out an investigation and how they unearth new information are both impacted by epistemology. In this study, the “intersubjective” (Morgan, 2007) and “relational” (Kivunja & Kuyini, 2017:35) epistemology was used, hence a variety of research approaches were utilised to achieve the objective of the study. Intersubjective epistemology emphasises the role of social interaction and communication in the construction of knowledge (Stolorow & Atwood, 1996).

The subjectivism approach facilitated a deeper understanding of user needs through interviews and observations, collecting valuable qualitative data directly from users. This integration of perspectives enriched the study's insights and decision support system development. The AI-enabled decision support artefact was designed after considering the perspectives and insights of multiple stakeholders, facilitating collaboration and shared understanding among decision-makers. By incorporating subjective elements, the system aimed to avoid individual biases and subjective limitations, leading to more comprehensive and holistic decision-making. In contrast, relational epistemology emphasises the importance of interpersonal connections and context in shaping knowledge and truth. The artefact was sensitive to the relational aspects of decision-making, recognising that the meaning and relevance of information may vary depending on the specific context in which it is applied. By embracing relational epistemology, the system will be more adaptive and responsive to the needs of different decision scenarios, enhancing its effectiveness in diverse real-world situations.

3.4.2 Ontology

The study of ontology focuses on the nature of reality (Creswell & Poth, 2018; Yilmaz, 2013). It considers the preconceived notions that academics have that something is logical (Scotland, 2012). Quantitative study presupposes the existence of a single, consistent, material reality (Yilmaz, 2013). It insists that there is just one reality (Slevitch, 2017). According to the findings of qualitative research, the nature of reality is complex, socially produced, and all-encompassing (Creswell & Poth, 2018; Yilmaz, 2013). Participants reconstruct reality based on their understanding of the context of that reality (Slevitch, 2017). The use of ontology provides researchers with assistance in data interpretation. Additionally, the ontological ideas of individuals have an impact on their capacity to formulate research questions, comprehend the significance of the questions, and analyse evidence. This study therefore subscribes to non-singular reality as explained by Kivunja and Kuyini (2017:35).

This approach is supported by Marcuse (1955:259) who states that an interpertivism philosophy encompasses ontologies emphasizing that it is not merely a methodological approach. Therefore, this research project aimed to develop an AI-enabled decision support artefact that embodies the principles of ontological perspective. By integrating ontological stance into the development process, the decision support system was designed to leverage practical experiences and the consequences of its recommendations in real-world scenarios. Through the application of ontological subjectivism, the AI-enabled decision support artefact will prioritise experiential knowledge and practical outcomes, adapting to various contexts and embracing interpretivism to accommodate diverse perspectives and beliefs. The system's decision-making process will be informed by the practical consequences of its recommendations, assessing their effectiveness and value, and evolving over time to reflect the dynamic nature of reality. This study created an innovative and adaptive AI solution that can effectively assist decision-makers in making informed choices based on practical experiences and real-world outcomes, ensuring the artefact's theoretical soundness and practical value in a range of decision-making scenarios.

3.4.3 Axiology

The study of research values is referred to as axiology. Research that is both positive and quantitative will differentiate between the facts and the values. Subjective values have the potential to mislead and impede the quest for the truth (Thurairajah, 2019). Subjectivity has a negative impact, while objectivity has a positive impact. When conducting qualitative research, the researcher is required to reveal their own beliefs and prejudices, as well as data that has been infused with value (Creswell & Poth, 2018). Moreover, the researcher acknowledges that both the researcher's voice and the voices of the participants are reflected in the narratives that were recounted. Axiology is vital since values are "ineluctable" in qualitative study results (Thurairajah, 2019). Furthermore, axiology is the study of how researchers prioritise different aspects of their research, such as participants, data, and audiences. Using the preceding three assumptions to get the axiological assumption (Creswell & Poth, 2018). The researcher is active in the organisational setting and thus the “necessary bias principle” applies as alluded to by Maarouf (2019:7). The AI-enabled decision support artefact was designed to consider ethical considerations, ensuring that its recommendations align with the case university’s values and moral principles. By incorporating axiology, the system will aim to make ethically responsible decisions and promote a positive impact on society and stakeholders. The adopted research philosophy for the study is summarised in Figure 3.2 below.

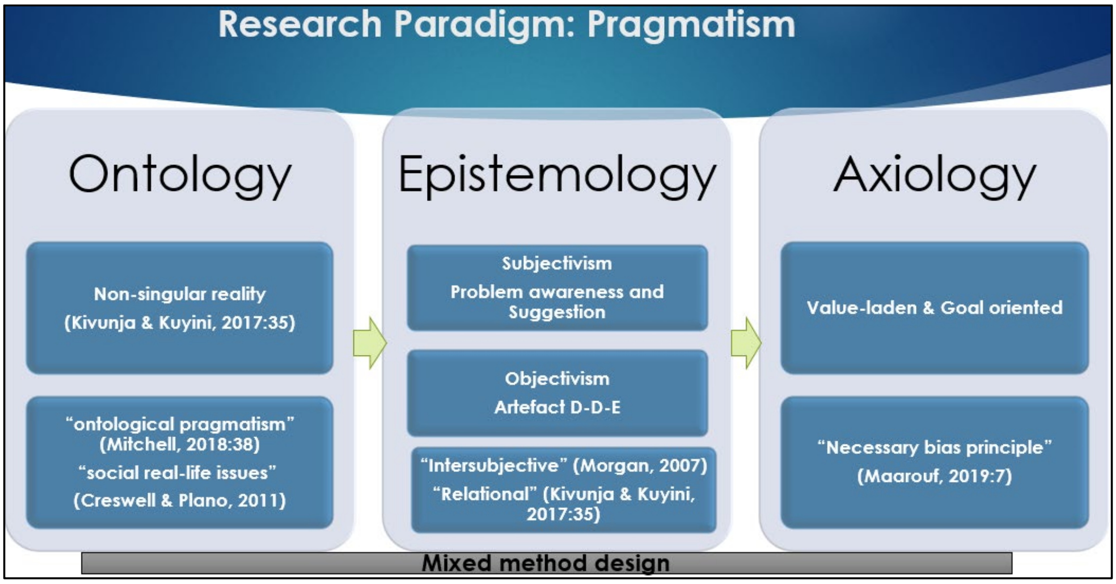


Figure 3.2 AIDSS Research Philosophy

3.5 Research Design

The research design creates a structural guideline for the researcher regarding theories, strategies, and instruments utilised during the research investigation (Athanasou *et al.*, 2012; DePoy & Gitlin, 2015). According to Creswell (2014), research design encompasses the comprehensive plan or strategy that researchers employ to address their research questions or examine their hypotheses. The way a research study's structure relies on the posed research question, the characteristics of the gathered data and the overall objectives of the study. Regnell *et al.* (2011) suggest that Design Science Research (DSR) is a research method based on outcomes and is frequently used in IS and IT with rules for evaluating and doing iterative testing. That is, a research design holds together different components of the research. Various research designs include case studies, surveys, action research and descriptive. Each of these designs is determined by the nature of the study, research question and researcher's set of beliefs and values in the collection, analysis, interpretation and use of data (Leedy & Ormrod, 2014). Design Science Research (DSR) creates innovative products that contribute to the expansion of human understanding. The goal of the DSR is to further the advancement of technology and science through the creation of novel artefacts that address pressing issues and improve the quality of life. The purpose of a DSR research project is to improve the capacities of both humans and organisations by way of the production of unique and inventive items (Hevner *et al.* 2008, Gregor & Hevner 2013).

3.5.1 Design Science Research

Design science research methodology (DSRM) refers to the research methodologies associated with this paradigm. It spans the methodologies of several research disciplines, for example information technology, which offers specific guidelines for evaluation and iteration within research projects (Leedy & Omrod, 2019). The idea of "science of design" was developed over half a century ago by Simon (1969), who highlighted the differences between natural science and design science. More specifically, Dresch et al. (2015) indicated that the obvious purpose of design science is to design; to produce something that does not yet exist, or to modify existing solutions to achieve better results. Design science research has been defined as "research that invents a new purposeful artefact to address a generalised type of problem and evaluates its utility for solving problems of that type" (Venable & Baskerville, 2012:142).

The nature of the problem at hand is neither exploratory nor explanatory but requires developing a new system for decision-making at a selected public-funded university. This study involves the design and development of an artefact that is AI-enabled to support decision-making in South African higher education institutions; therefore, the Design Science Research design is used. The current operational decision-making processes at the selected university's ICT department are not synchronised and are done in silos. Decisions are disjointed, and there is a lack of coherence between units; for instance, decisions made by the network unit may not align with those of the infrastructure unit, and the servicedesk may not coordinate decisions with the enterprise resource planning unit. This fragmented approach extends to various aspects, including Business Process Automation (BPA), teaching and learning facilities, and IT operations, resulting in a dispersed and uncoordinated system. Thus, the researcher has elicited users' perceptions of the current information systems and how they expect the challenges to be addressed. An AI-enabled solution is designed and presented to participants for their feedback. Feedback from participants is essential to refine the artefact, which is part of DSR. The DSR approach aims to solve a decision-making problem through an artefact (Livari & Venable, 2009). The challenge at hand pertains to the transformation of the ICT department through the provision of actionable insights. This necessitated a departure from traditional decision-making, reliant on intuition and past experiences towards an analytical data-driven approach. The above stated problem warranted the DSR methodology to produce a solution that would be widely acceptable. Peffers *et al.* (2007) posit that DSR allows the researcher to create and design information technology (IT) artefacts to solve an organisational problem. Design Science Research (DSR) is a research methodology that aims to develop and evaluate artefacts that address practical problems in the field of information systems (Hevner *et al.*, 2008). The approach involves a problem-solving process that uses scientific and engineering methods to create and evaluate innovative solutions to real-world problems. DSR is in the field of information systems because it allows researchers to develop and evaluate practical solutions that address real-world problems. It is particularly useful in situations where traditional research methods, such as quantitative or qualitative research, are not sufficient to address complex problems that require innovative solutions (Hevner, Ram, March & Park, 2008). March & Smith (1995) stress that the utilisation of DSR supports the creation and advancement of artefacts, encompassing software systems, decision support tools, and information management systems. The approach is applicable in fields such as healthcare, finance and education. Key advantages of DSR include researcher ability to create practical solutions that can be immediately applied to real-world problems. The approach also allows researchers to evaluate the effectiveness of the artefacts they develop, which can lead to further improvements and refinements.

In this study, the problem is the decision-making processes done in silos. Therefore, adopting the DSR will help rigorously design an AI-enabled artefact (system) to solve the issue at hand. Hevner *et al.*, (2008) concur by stating that DSR involves a thorough examination of the artefact's utilisation and performance. The authors outline how DSR is conducted, evaluated and presented by describing its boundaries and a set of guidelines. Pertinent to DSR methodology is the production of an artefact to solve an organisational problem and improve decision-making. With reference to the objective of this study, the developed artefact will contribute to its application within the context of the university's needs. Therefore, the design construction contributes to the knowledge base through evaluated methods, constructs and improved design science knowledge (Hevner *et al.*, 2008).

The AIDSS conceptual framework (adapted from Kuechler & Vaishnavi, 2008) depicted in Figure 1.7 facilitated the design of an AI-enabled decision support system as follows:

Step 1: The first step is identifying an organisational problem and motivating why it should be solved as articulated in research objective one "*To determine how various decision-making elements affect decision-making within the ICT department at the university*". A clearly defined problem statement that warranted further investigations on its effects if it is not resolved.

Researchers can read from recorded works and literature to better understand the problem's nature. The problem in this study is the inability of management and employees to make informed decisions based on the current decision-making processes, which are fragmented due to silos and disparities in systems and large amounts of data.

Step 2: Defining the objectives of a solution is an essential step for the researcher to decide on a better artefact to accomplish in line with the defined research problem. Some problems might require different trials of solutions before an ideal artefact is designed. Step 2 is a solution-centred initiative, an AI-enabled decisions support system that could address operational challenges in response to objective two "*To determine how operational decision-making occurs within the ICT department at the university*".

Step 3: Design and development: The prototype artefact was designed and presented to users, as aligned to objective three "*To assess challenges faced by decision-makers when making operational decisions within the ICT department at the university*". The artefact was tested and evaluated to determine if it addresses the problems raised by users.

Step 4: Evaluation: In this step, the usefulness of the artefact was measured against its ability to solve the problem and meet the research objectives. If the artefact fails to meet the expected goals, it can go back to step 3. The DSR approach allows for IS evaluation, which allows iteration before proceeding to the next step. The artefact must align to the users' expectations and satisfy objective four "*To develop an AI-enabled decision support system to support operational decision-making within the ICT department at the university*".

Step 5: Conclusion: the last step of the DSR is to conclude and communicate the results of the developed AI-enabled decision support system- for higher education through the lens of scholarly and professional publications. This process entails demonstrating how the artefact should be used at the selected public-funded university. If users are satisfied with the system, then implementation on a full scale can commence.

Kuechler and Vaishnavi (2008) state that it is crucial to follow the above steps in their logical order to yield the desired results. While Peffers *et al.* (2007) argue that it is unnecessary to follow the steps in their logical sequence, the nature of the problem at hand may determine how an artefact could be developed. Given the contrasting views, this research adopted a problem-centred approach because there is an existing problem, and literature concurs with its existence; thus, a logical sequence by Kuechler and Vaishnavi (2008) has been followed through the conceptual framework in Figure 1.7.

The adopted conceptual framework served as the backdrop for this research project. The initial phase of the research involved identifying and justifying an organisational problem, underscoring the significance of a clearly defined problem statement that necessitated further investigation. Following this, the focus shifted towards defining the objectives of a solution, particularly in dealing with intricate issues that may require multiple iterations. Subsequently, the research progressed into the phases of designing, developing and evaluating the AIDSS prototype artefact aimed at addressing the identified problem. Evaluation was a critical step, where the artefact's effectiveness in problem-solving and alignment with the organisation's strategic objectives was assessed. The research culminated in the dissemination of results and a demonstration of how the artefact can be effectively integrated into the selected public-funded university, with full-scale implementation contingent upon user satisfaction. This project acknowledged the centrality of predictive decision-making processes, while also examining the technological infrastructure, application and capabilities to explore how AI tools can enhance predictive decision-making. The ultimate outcome of this research project significantly contributed to the design and development of the artefact AIDSS, aligning it with the functional requirements, ICT department and organisational goals within the selected university setting.

3.6 Research Methods

The term "research methodology" refers to the procedures that should be followed when conducting research as well as the tools that are necessary to gather and investigate data to find answers to questions raised by the research study (Saunders *et al.*, 2012). Rehman and Alharthi (2016) defined methodology as the process that advises a researcher on the selection of research methods. This includes participants, data gathering, research instruments, and data analysis. Methodology describes the process and manner in which a research will be conducted, and informs the researcher of the type of required data for a study, and determines data collection techniques that will best fit the study purpose (Krauss, 2005). Rahi (2017) asserts that methodology refers to the methodological question that guides the researchers how to study the world. Generally, the methodology clearly states the process flow of the study in order to acquire knowledge about a research problem (Chen & Hirschheim, 2004). That is, a researcher determines how they will obtain the required data and knowledge, which enables them to answer the research question and in this manner contribute to the body of knowledge (Kivunja & Kuyini, 2017).

3.6.1 Qualitative Research Method

Venkatesh *et al.* (2013) concludes that inferring people's viewpoints on a topic and getting insight into the subjective realities of participants are both important purposes that can be served by qualitative research methodologies. During qualitative analysis, "objective and methodical conclusions about message qualities" were reached (Du Plooy and Du Plooy 2009). The qualitative investigation was carried out at the same time as the quantitative investigation. In general, qualitative data is significant and believable; but, because of the limited sample sizes of most qualitative investigations, it is difficult to generalise the findings of these studies to a larger population (Teddlie & Tashakkori, 2009). Research methods such as interviews, documentation, and observation are utilised in qualitative studies (Fusch *et al.*, 2018). Interviews, written documentation, and direct observation are all components of qualitative research (Vindrola-Padros & Johnson, 2020). Individuals are allowed to discuss their experiences in their own words during qualitative research (Lee *et al.*, 2017). The focus of qualitative research is on human and organisational behaviour, and its findings are reflective of human experience (Shekhar *et al.*, 2018).

To gain a deeper understanding of a topic and locate specific problems, qualitative research is often employed (Palaganas *et al.*, 2017). According to Mohajan (2018), one effective strategy for evaluating a challenge facing a company is to watch people in the environments in which they naturally behave. In qualitative research, each subject is questioned about a single issue using the same set of questions. If the study of the data yields no new information, scientists might decide to stop collecting data (Richards *et al.*, 2019). Interviews with participants will continue until they are unable to contribute any more data that can be used in the development of an AI-enabled decision support system for South Africa. The degree to which a study has attained data saturation reveals its reliability, credibility, and applicability (Saunders *et al.*, 2018). The investigation does not produce any new information or topics, and the facts are complete (Hennink *et al.*, 2017). Saturation of the data will be achieved using processes such as semi structured interviews, literature, and observations. The development of an AI-powered decision support system for South African HEIs made use of interviews that followed a semi-structured format (Appendix E). The researcher generated consistent communication through the process of confirming data provided by participants (Anderson, 2017).

Open-ended questions were formulated for the interviews; therefore, the researcher was able to address the “what”, “how” and “why” type of questions. Participants shared their personal experiences of events as they occurred in a natural setting. Research data was contextualised to a real-life setting. In order to develop a general principle, the researcher used accurate and unbiased information during data collection (Guest, Namey & Mitchell, 2013). The general principle for studies involving human beings and organisations is that researchers collect concerns, experiences related to a phenomenon, therefore, qualitative research approaches are ideal (Kumar, 2018).

The objective was to develop an Artificial intelligence-enabled decision support system to support decision making in the ICT department in a selected public-funded university in South Africa. To gain a comprehension of the problem at hand, a quantitative-qualitative method was combined, the researcher first conducted semi-structured interviews with selected participants and then developed the artefact and thereafter conducted the questionnaire. These data collection processes helped to understand and interpret the decision-making processes, whilst studying the participants in their natural setting, that is in their work environment, a key component of mixed-method research (Creswell, 2014).

In this study, a mixed method was used. Case studies and surveys frequently employ a combination of qualitative and quantitative methods, as noted by Van Wyk (2015). This blended methodology is particularly effective when researchers aim to address specific research questions that require comprehensive and detailed information. It involves a strategy that combines Quantitative-Qualitative techniques for data sampling, measurement and analysis as discussed by Krammer (2011:52). Utilising the Quantitative-Qualitative method offers advantages, including the ability to generate and explore theories, validate findings and achieve examination of a research topic both in terms of breadth and depth as emphasised by Teddlie and Tashakkori (2009). The findings obtained from a case study are often utilised to make transferability in broader contexts, as highlighted by Rodong and Sese (2008).

A guide for semi-structured interviews was developed by incorporating insights from a comprehensive review of relevant literature and including additional focused questions (see Appendix E). These interviews took place between June 1 and July 30, 2023, and followed a semi-structured format. Using convenience sampling, ten participants who are management decision-makers were approached from the ICT department of the university under study to participate in these interviews. Table 3.1 below shows some of the profile of participants in no particular order.

Table 3.1: Participant roles (author, 2023)

Profile	Responsibility
Participant 1	Responsible for managing and coordinating responses to IT incidents ensuring resolution and minimal disruption to operations.
Participant 2 & Participant 3	In charge of overseeing the network infrastructure, troubleshooting issues and designing network solutions to enhance connectivity and performance.
Participant 4	Supervise a service desk team who provide telephone assistance, assigning tasks to team members and tracking the progress of support tickets
Participant 5 & Participant 6	Experts while mentoring junior staff members and providing innovative solutions for complex technical problems
Participant 7 & Participant 8	Provide end-users with technical support regarding hardware, software, and networking issues. Troubleshoot and resolve technical problems, install and upgrade software, configure hardware devices, and ensure smooth operation of desktop systems
Participant 9	Is responsible for automation. Analyses business processes thoroughly identified areas of inefficiency and designs optimised workflows to enhance efficiency.
Participant 10	Manages company networks, systems, and software. Leading IT teams and aligning IT initiatives with business goals and departments.

3.7 Theoretical Framework

It has proven difficult to agree on a common taxonomy for decision-making theories (Thomas and Musa, 2020). Chigada and Ngulube (2015) state that theory is imperative in research for various reasons such as it justifies the research questions, explains the context of the problem and organises the research findings. In this study, theory will be used to answer the research questions (Leedy & Omrod, 2019). The two main categories of decision theories, as described by Ahmed and Omotunde (2012), are the theory of decision-making with normative and descriptive goals. Normative or prescriptive decision theory, offers templates for the best decision-making, is a component of decision theory. The descriptive decision theory that results from observation is also included (Anderson, 2017). Both theories may be utilised with many technologies; for example, many corporate software systems are supplied by vendors as decision support tools, therefore it stands to reason that their engineers would gain from studying decision theory. Like this, researchers are intensively investigating decision theory to build machine learning tools and artificial intelligence technologies.

One way to think about this is that a careful examination of decision theory may expose the parallels and differences between human and machine decision-making, inspiring scientists and engineers to bridge the cognitive gap between them. As opposed to explaining how decisions should be made, descriptive theory sheds light on the decision-making process itself. This research study employs the descriptive theory. Many academics have also divided the theories into rational and irrational categories (Gigerenezer, 2001; Hansson, 2005; Oliveira, 2007). "Optimising, normative, omniscience and internal consistency" are the four characteristics that Gigerenezer (2001) identifies as unique to rational theories and useful in distinguishing them from irrational ones. Like rational theories, irrational ones can be identified by their use of cognitive elements such as sentiments, mimicking, and cultural standards. and their lack of optimisation, description, search and ecological rationality (Anwar, 2014). The questionnaire was adopted from Kao et al (2016) and constructed with additional questions based on the Goal Question Metric (GQM) approach aligned to the main research question and four study's research questions, encompassing a comprehensive set of key performance indicators.

3.7.1 Economic Theory

According to Edwards (1954:380), economic theory pertains to the process through which an individual anticipates and evaluates the alternatives available to them within a given set of circumstances. Theories pertaining to decision-making have undergone evolutionary development and frequently employ sophisticated mathematical logic (Edwards, 1954:380). Time, effectiveness, uncertainty, ambiguity, complexity, and human biases are other factors that influence decision-making (Dane *et al.*, 2012,). Decision making theory and AI are intertwined: "look ahead, uncertainty, and (multi-attribute) preferences for decision theory; diagnostic representation and processing of the recorded states for AI." (Pomerol 2018). Jarrahi (2018) reports that AI has the potential to assume, support, and augment the human decision-making process in the context of organisational change and decision-making challenges. AI may play three different roles in a company when it comes to decision-making: it can support the management, take the manager's place as the decision-maker, or even operate as the manager's forecaster (Dejoux & Léon, 2018:199).

3.7.2 Architectural Design Theory

The fundamental goal of this study is to create a decision-support system powered by artificial intelligence and adapted to the unique requirements of institutions in South Africa. To successfully meet institutional difficulties, the system's potential will be optimised via a well-planned architectural arrangement (Blem *et al.*, 2015). The study will examine the system's architecture, how it relates to the study's aims, and its individual parts as shown in Figure 3.3 below. Using Information Systems Architectural (ISA) design theory, the study will examine the difficulties encountered by the case university and their decision-making processes in detail to guarantee the system's applicability. Protecting sensitive institutional data will also need attention to data privacy and security issues. The system's architecture and features may be fine-tuned based on input from the people who will be using it. Chapter Four and Six provide a detailed account of how the study employed the ISA design theory to achieve the aim of the study.

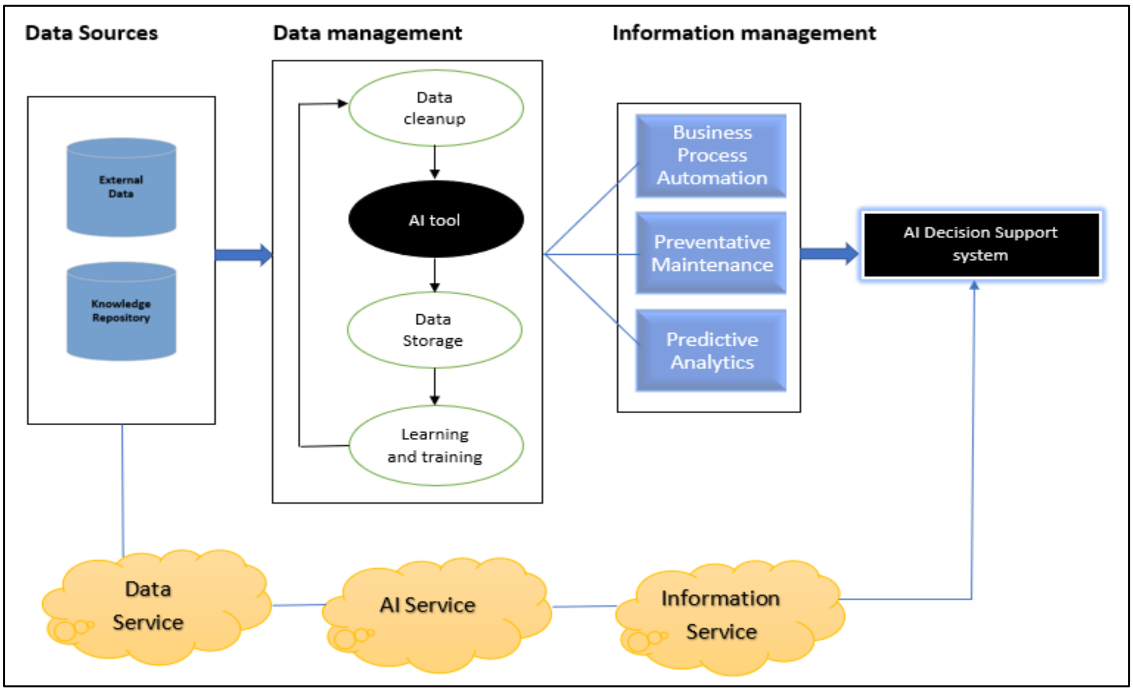


Figure 3.3 Architectural design for AIDSS

3.8 Study Setting/Case study

Study setting refers to the physical, social, or cultural environment associated with the context of the research study. It is an important aspect of a research study because the setting can influence the results of the study and affect the generalisability of the findings (Polit & Beck, 2008). The setting of a research study can vary depending on the specific research question under investigation. For example, if the research question involves examining the impact of a new educational intervention on student outcomes, the study setting may be a school or a specific classroom within a school. Leedy and Ormrod (2014) state that when selecting a study setting, researchers must consider a range of factors, including the availability of participants, access to data or materials and the feasibility of conducting the study in a particular setting. The study setting must also accurately reflect the population under study to ensure that the results can be generalised to a range of people. It is important for researchers to carefully document the study setting to provide context for their findings and to allow for replication of the study in the future. This documentation may include a description of the physical environment, the studied population, and any relevant cultural or social factors that may have influenced the study results (Creswell, 2014).

This study adopted a case study research design because data were collected and contextualised to a specific institution of higher learning. Yin (2014) defines a case study as a detailed study of a specific subject, such as a person, group, place, event, organization, or phenomenon. Case studies are commonly used in social, educational, clinical, and business research. A case study is one of the most extensively used strategies of qualitative social research. Over the years, its application has expanded by leaps and bounds, and is now being employed in several disciplines of social science such as sociology, management, anthropology, psychology and others.Case Studies are a qualitative design in which the researcher explores in depth a program, event, activity, process, or one or more individuals. The case(s) are bound by time and activity, and researchers collect detailed information using a variety of data collection procedures over a sustained period of time.

Figure 3.4 Map of showing Eastern Cape (Britannica, 2023)

The context of this study was the department of a specific university located in the Eastern Cape province of South Africa as seen in Figure 3.4.

3.9 Population of the Study

The population in a study context denotes the collective of individuals, objects, or events that are the focus of a research study. The population of this study consists of the decision makers in the ICT department including senior technicians, managers, and directors in the selected study area. relevant demographic or clinical factors that may impact the study findings (Creswell, 2014). The target population for this study were more than 200 managers occupying various portfolios within the university. Given the exploratory nature of the study, it was not feasible to include all 200 managers in the study, therefore, a sample was selected.

3.9.1 Sampling Technique

A sample relates to a selection drawn from a population group and the study findings enabling the generalisation of findings to the population (Leedy & Ormrod, 2014). When selecting a sample for a study, researchers must ensure that it is representative of the community under investigation to ensure the external validity of the study (Polit & Beck, 2008). The research report should clearly define the population, including a description of Leedy and Ormrod (2014) conclude that sampling is an important aspect of research design because the accuracy of the study findings depends on the quality of the sample selected. The sampling method is a process used to select a portion of individuals or items from a population to be included in a research study. The goal of sampling is to obtain a sample that accurately reflects the characteristics of the population being studied. Various sampling strategies exist, encompassing both probability sampling and non-probability sample methods. Probability sampling is a method in which a sample is chosen from a population in a random manner, with the aim of guaranteeing that each member of the population is equally likely to be chosen. In comparison, non-probability sampling does not entail the process of random selection and may be based on convenience, judgment, or quota sampling (Polit & Beck, 2008). The selection of a sampling technique is based upon the research questioning, the makeup of the population under investigation, and the resources at hand for the study. Probability sampling is generally preferred because it allows for greater accuracy and generalisability of the study findings (Creswell, 2014). When describing the sampling technique in a research report, researchers should provide a clear and detailed description of the sampling method used and any potential limitations or biases in the sample selection process. Non-probability sampling techniques may be used when probability sampling is not feasible or practical, but these methods may introduce biases into the study results (Creswell, 2014).

The study undertook convenience sampling. Convenience sampling is a sampling method that does not involve probability and entails the selection of individuals who are conveniently available or easily accessible to the researcher (Kumar, 2019). The author further states, one of the main advantages of convenience sampling is its ease and speed of implementation, as it does not require complex sampling designs, specialised personnel, or extensive resources.

Convenience sampling also allows researchers to gather data quickly and efficiently, making it a popular choice for exploratory or pilot studies, or when testing new research instruments. Convenience sampling enables the researcher to conveniently select decision-makers in the ICT department for the study. Exclusion/inclusion criteria focused on the participant being in the employment of the institution for a minimum period of 5 years, working in the information technology domain either as a manager, supervisor, technician, service desk manager or business process management. If the participant did not meet these conditions, the researcher did not consider them. Participants had to have a technical exposure and understanding of the ICT landscape.

3.10 Data Collection in DSR

The study developed an AI-enabled decision support artefact, as such, it incorporated both primary and secondary sources of information. According to Young *et al.* (2018), researchers make use of both primary and secondary sources while conducting collection, analysis and interpretation of data. Semi-structured interviews, observations, and questionnaires are the three methods used to extract primary data from decision-makers in the ICT department. Emailed invitations sent to potential respondents requested participation as soon as possible. By reviewing existing research literature in Chapters Two, the goal was to identify patterns, trends and valuable insights that could inform the study's objectives. This process also helped identify areas where knowledge is lacking, potential points of divergence and emerging themes, within the AI and DSS field. Chapters Four and Five provide detailed data analysis. Data gathering tools included literature review, interviews, questionnaires and observation.

Literature review: This study utilised secondary data as a means of gathering information that was previously published or collected by other researchers or organisations in the domain of Artificial intelligence and decision support systems. The literature review involved an extensive search for information from a wide range of sources, including academic journals, books, and reports. The information gathered was used to explore the research objectives and to provide a foundation for the study.

Face-to-face interviews: For this study, interviews proved to be an extremely useful tool for gathering essential information regarding the application of ICT at the institution that was selected. The interviews were conducted with the aim of extracting participants' knowledge, experience, and opinions, with a focus on establishing the requirements within the problem domain for the development of the artefact. A pilot study was conducted with two staff members prior to conducting the interviews at full scale. The results of the pilot study are clarified in Chapter Four. During the process, the researcher adhered to interview procedures, also known as protocols. Protocols for conducting interviews encourage standardisation, reliability, and transparency (Edwards, 2017).

Observations: Observational data involves descriptive observations and the ability to make inferences from body language and behaviour (Yin, 2018). In this study, the researcher observed ICT personnel in their work environment, incorporating their own experiences and observations to construct the research narrative as discussed in Chapter Four. Saunders, Lewis and Thornhill (2019) state that observations are used to study people's behaviour whilst in action. Observations of the existing environmental practices provided insights and guidance during the artefact development process.

3.10.1 Data Gathering

Participants were asked open-ended questions designed to elicit rich and detailed responses regarding their experiences, perspectives and insights related to decision-making. The interviewees that were chosen are derived from the expected target population for the study. The interviews were recorded using audio the recording device and later transcribed verbatim to capture the details of the conversations. Transcription allowed for a thorough examination of the data, enabling the researcher to identify recurring themes, patterns and insights relevant to the research objective. Subsequently, initial coding was conducted to systematically tag segments of text that were relevant to decision-making, capturing key concepts, ideas and experiences shared by the participants. Through this process, preliminary themes began to emerge, representing overarching concepts or phenomena related to the use and impact of the decision-making processes. These themes were further refined and developed through iterative analysis, culminating in a comprehensive understanding of the role and significance of decision-making in the ICT department.

To ensure consistency in the questions asked, the researcher used an interview guide (Appendix E) which contained the questions that were posed to the interviewees. These interviews were conducted with management decision-makers in the ICT department. This is mainly because the researcher wanted to capture the perspective of the management as it affects whether or not different technological advancements are integrated into the ICT department. The initially intended number of people for the study was thirteen participants but the researcher only managed to obtain feedback from ten participants. In the findings two of the participants are female whilst the other eight are male. The participants are also of varying management levels. This allowed the researcher to attain a fuller analogy of the work environment and how it affected decision-making.

Thematic Data Analysis

Thematic analysis is a crucial step in the qualitative data analysis process, occurring after coding and involving the identification of themes or patterns within the data. This method entails grouping data into logical categories based on commonalities or recurring concepts, which are then named to represent overarching themes. Working from codes to themes allows researchers to extract meaningful insights from the data, facilitating a deeper understanding of the phenomenon under study. As highlighted by Rule and John (2011:78), the discussion of these themes and the relationships between them are central to interpreting the case. By systematically analysing and synthesising the identified themes, researchers can uncover underlying trends, perspectives, and implications within the data, ultimately contributing to the richness and depth of the research findings.

Theme Generation

The themes were derived from interview responses from the participants in relation to the objective of the research, which was to illustrate how effective the adoption of AI would be in the ICT Department. Below is a description of objectives and themes.

Theme Review

The themes that are selected for a study are based on the research objectives. This is because the research objectives form the basis of the study. The semi-structured interviews also contributed to the themes and are further explained in Chapter Four. The themes that were explored for this study are:

1. How various decision-making elements affect decision-making within the ICT department
2. Analyse how operational decision making is performed within the ICT department
3. Challenges faced by decision makers within the ICT department
4. The development of an AI enabled decision support system

By using thematic data analysis, the researcher was not merely summarising the data, but making sense and interpreting it. The researcher followed a six-step approach to data analysis. The researcher's involvement in the interview process exposed the researcher to the data. The researcher read and re-read the interview transcripts, making notes of early impressions. The third step required the program to identify the themes- patterns that were interesting about the research question. The researcher examined the codes to ascertain if they fitted well into themes. These codes were organised into broader themes, resulting in the review of themes (step 4). There were modifications and development of preliminary themes to determine if the themes were sensible. In the fifth step, the themes were defined with the objective of refining them. Once satisfied with the refined themes, the researcher proceeds to report the findings in the form of a report.

3.10.2 Research Evaluation

Once a research project is completed, it is crucial to establish the credibility and integrity of the research findings. Research evaluation serves as a necessary step to validate the methods, data, and conclusions of the study, ensuring that they are robust, reliable, and trustworthy. Through submitting the research to a comprehensive review process, it becomes possible to identify and rectify potential biases, restrictions or errors, enhancing the overall quality and credibility of the research. This evaluation can be conducted through various means such as peer review, expert feedback, replication studies or external audits. The goal of research evaluation is to maintain the level of precision and contribute to the progress of knowledge in the relevant discipline. This study produced a prototype for an Artificial intelligence-enabled decision support system for higher education institutions in South Africa. The means of evaluating this research project are described in the next section.

3.10.3 Goal Question Metric

As alluded in Chapter One, the effectiveness of the artefact must be measured to establish if there is an improvement in the operational decision-making process at the ICT department; therefore, a Goal Question Metric (GQM) approach was used. Caldiera and Rombach (1994) posit that the GQM requires the researcher to specify the research project's objectives, link those objectives to the data to be collected that will define the objectives, and provide a structure for analysing the data. The GQM approach serves as a comprehensive framework for this research project, ensuring that the goals, questions, and metrics are well-defined and aligned with the study's objectives (Koziolek, 2008). By applying GQM, the study systematically evaluated the effectiveness of the AI-enabled decision support system in improving operational decision-making at the ICT department of a HEI in South Africa. The combination of well-formulated questions and relevant metrics provided valuable insights and data to draw objective conclusions about the system's performance and its potential to enhance decision-making processes. The questionnaire was adapted from Kao et al., (2016) and constructed with additional questions based on the GQM approach, encompassing a comprehensive set of key performance indicators.

3.11 Trustworthiness

According to Stead (2001:136), the authenticity of the data as well as its dependability and trustworthiness pertain to "the degree to which a research design is scientifically robust or conducted appropriately." In this qualitative study, it is important to ensure that research findings are trustworthy to mitigate inaccurate reporting. Saunders et al (2016:381) state that some processes should be undertaken to ensure that research results are credible before being published. A pilot study was conducted with two sample elements to ascertain if the research instrument could be used in other settings and produce similar results under the same conditions (Creswell, 2014). All research processes were documented, and the documents kept in a safe for future references. It is important to keep an audit trail of everything if the study is challenged.

Additionally, the research process was presented in a transparent and clear manner, facilitating readers' understanding of how the study was conducted. Lastly, a diverse range of research approaches was utilised, each tailored to address specific aspects of the study's objectives. This inclusive and comprehensive approach allowed the researcher to achieve a greater level of comprehension regarding the decision-making process. In the case university and enriched the research findings. Embracing the intersubjective and relational epistemology, along with the diverse research approaches, enhanced the study's robustness and contributed to the overall rigor and depth of the research. By adhering to these practices, the research aimed to uphold the accuracy and dependability of the data, thereby reinforcing the credibility of the study's outcomes.

Credibility refers to the interpretation and presentation of participants' perceptions as reported by participants (Anney, 2014:276). According to Kalu and Bwalya (2017:50) credibility of qualitative research can be achieved through methods such as interviews or focus group discussions (Kreuger & Casey 2009; Padgett, 2016; Kalu & Bwalya, 2017:50). The credibility of the study was enhanced through sharing of personal experiences during the telephonic interviews. After collecting all data, the researcher went back to the participants to verify if the results were a true reflection of what was discussed during the telephonic interviews.

Transferability of a study refers to the evidence that the outcome of one study can be applied in another context involving different participants (Pandey & Patnaik, 2014:5748; Anney, 2014:278). The techniques applied to support the transferability of this study included the sharing of comprehensive information about the phenomenon, the site and population studied and keeping and maintaining records of field notes in any format (Amankwaa, 2016:122). The pilot study was conducted to ascertain if the research instruments were plausible and could be used in a different environment, produce the same results under the same conditions.

Dependability in qualitative research and reliability in quantitative research are regarded as the same however, dependability is evaluated by means of non-numerical data whereas reliability is measured through numerical data (Mabeba, 2018:54). According to Anney (2015:18) participants of a qualitative study are utilised to evaluate the findings, analysis and recommendations of the research to ensure that it is a true reflection of the information collected from participants. The researcher kept an audit trail of documents, original data, notes from the interviews and voice recordings of the interviewees. Data were recorded to reduce the inconsistencies (Moon, Brewer, Janichowski-Hartley, Adams & Blackman, 2016). The use of the interview protocol allowed the researcher to gather relevant data which enabled to address the research problem; thus, the research instrument was dependable to fulfil the completion of this research project.

Confirmability denotes steps taken by the researcher to prove that the findings of the research are based on the data that was collected from subjects not from his or her own biases (Bwalya, 2017:51). *Confirmability is established when credibility, transferability, and dependability are all achieved* (Nowell1, Norris, White & Moules, 2017:03). The researcher described in detail the DSR, its implementation, and provided an audit trail of note documents and evidence of the decisions and choices made regarding the theoretical and methodological issues throughout the study (Bwalya, 2017:51). The sharing of this information was intended to give readers of the research a thorough understanding of the chosen methods and decide on whether they are effective or not (Creswell, 2018). In addition, the researcher verified the results with all participants to ensure that a true reflection of participants' inputs was captured. This was an important step to ensure that correct results were published.

Authenticity is the degree to which a range of truths in a research study are justifiably and faithfully publicized by researchers (Polit & Beck, 2014:1251). The criterion of authenticity was addressed through the selection of suitable people for the study sample (Connelly, 2016:436). Further, the researcher throughout the process conferred to all participants the respect they deserve.

Before publishing the results, the researcher approached all participants to validate if the results were a true reflection of their responses.

3.11 Ethical Considerations

According to Glass *et al.* (2018), when conducting research, the researcher is required to consider and act on a variety of ethical considerations. The researcher oversees ensuring that the participants are not injured in any way, that they have given their informed consent, that the study has been approved by both the ethics committee and the site organisation, and that their identity and confidentiality are maintained. Before undertaking the study, the Cape Peninsula University of Technology approved the study and granted ethical approval. The selected public university, which is the research site for the study, was then approached for the gatekeeper's permission to collect data from its staff members. As alluded in Chapter One, all participants who took part in the study were asked for informed consent. The study ensured full disclosure of information to participants, including the researcher's details and the study's purpose, allowing participants to make informed decisions about their participation. Privacy and confidentiality were maintained by excluding personally identifiable information during interviews and obtaining participants' consent before sharing any information. Participants were given the freedom to withdraw from the study without any consequences, and the study emphasized integrity, honesty, and the absence of inducements for participation. The research design also adhered to regulations regarding the Protection of Personal Information Act (POPIA).

3.12 Chapter Summary

This chapter presented the adopted research methodology which facilitated data collection from the decision-makers in the ICT department regarding the study. This chapter provided a thorough review of the study technique and how it was carried out. The research was conducted utilising a pragmatism approach. Furthermore, an explanation of the data analysis procedure has been provided. The study was conducted in a selected department in the Alice town, South Africa. The population of the study consists of the decision makers in the ICT department including senior technicians, supervisors, managers, and a director in the selected study area. A convenience sampling was adopted as the sampling technique. Interviews, questionnaires, observations, and a review of the relevant literature all contributed to the gathering of data. The data collected through the questionnaire were captured online and analysed using SPSS. While the information obtained through interviews and observations was subjected to theme analysis for interpretation. The results of the interviews and observations are going to be detailed in the following chapter, which is Chapter Four.

CHAPTER 4: RESULTS

4.1 Introduction

In this chapter, step one of the DSR process is explored, which involves identifying an organisational problem and providing reasons for its resolution. The data used for this step was gathered through interviews with ICT personnel to extract the dynamics of the problem. Interview data was explored using thematic analysis. Data analysis is the process of going over data and seeking to get as much insight into the data as possible by going through the data. It comprises evaluating, cleaning, transforming, and modelling data to locate useful information (Koomey, 2016). It's a means of inspecting the data for abnormalities, repeating significant computations, validating totals, and investigating the relationships between the numbers (Koomey, 2016). The researcher went over the data looking for patterns, trends and systems, as well as any ideas that may emerge that might help corroborate the variables in accordance with the research objectives. This necessitated analysing the study data for specifics that may be useful in producing an effective response to the research questions (Kumar, 2017).

The primary objective of this study was to develop an AI-enabled decision-support system tailored to the university's ICT operations. As such, the analysis aims to shed light on the intricate landscape of decision-making within the department and to draw connections between these insights and the overarching goal of system development. The study engaged in open discussions with individuals occupying management roles within the ICT department. These interviews, conducted with meticulous attention to detail, provided a nuanced perspective on the dynamics of incident management, collaboration, and coordination.

Moreover, the researcher sought to unravel the intricate layers of operational decision-making processes within the university's ICT domain. The step-by-step methods employed by each stakeholder in response to incidents were scrutinised. By doing so, the study not only uncovers the practical pathways of decision-making but also highlights the interplay between roles and the communication flows that govern this vital aspect of ICT operations. The challenges inherent in decision-making constitute another critical aspect explored in this analysis. By engaging stakeholders in conversations about the obstacles they face when making operational decisions, the researcher gains insights into the real-world constraints that impact efficiency and effectiveness. Furthermore, the alignment of decision-making with the university's organisational goals is a lens through which this analysis examines the broader implications of decision processes.

4.2 Results of Pilot Study

During the pilot study, the interview questions were validated to confirm that they elicited relevant and meaningful feedback from the participants. Jackson (2008:71) defines validity as the extent to which a measuring instrument accurately assesses the intended subject or attribute it purports to measure. At the outset, ten interview questions were developed for the study. Two personnel who are middle level managers in the ICT department were then approached and invited to participate in the pilot interview. During the pilot study, the questions were assessed for clarity and ease of comprehension, resulting in the identification of three questions that were found to be complex or ambiguous. In conducting the study, it was imperative to ensure that data collection methods were robust and reliable. Through this rigorous process, the researcher identified three questions that were found to be complex or ambiguous, potentially compromising the quality and accuracy of the data gathered. To maintain the integrity of the research findings, a proactive decision was made to remove these three questions from the interview. By doing so, the researcher aimed to enhance the overall clarity and effectiveness of the data collection process, ultimately bolstering the credibility and validity of the research outcomes. This strategic approach demonstrates unwavering commitment to conducting rigorous and high-quality research, ensuring that findings accurately reflect the complexities of the subject matter at hand. To compensate for their removal, secondary data sources were utilised to address the areas covered by those questions, ensuring that the study maintained its comprehensiveness and integrity. The three excluded interview questions were:

- Can you discuss any external factors, such as changes in technology or regulations, that impact decision-making?
- How do you plan to address potential concerns or resistance from staff regarding adopting an AI-enabled decision support system for decision-making?
- What challenges do decision-makers face when they make decisions?

Secondary data severally addressed each of these questions.

Can you discuss any external factors, such as changes in technology or regulations, that impact decision-making?

The rapid pace of technological innovation has had a considerable impact on the IT operations, which has led to significant adjustments in the way decisions are made in such departments. The research that was carried out by Amoako *et al.* (2021) showed that the implementation of artificial intelligence (AI) into decision-making systems led to a significant improvement in the accuracy and efficiency of IT operations. This demonstrates that AI has the potential to transform the processes that are used to make decisions.

Decision-makers in IT teams need help evaluating and selecting appropriate technologies due to the increasing complexity and interconnection of technical infrastructures. Rodgers *et al.* (2023) highlighted the significance of technology evaluation frameworks in terms of their role in facilitating effective decision-making. To facilitate the process of technology selection for companies and ensure that the selected technologies are in line with their goals and the resources they have available, frameworks are of the utmost relevance and are of utmost importance. Individuals in positions of power can make well-informed judgements and avoid the potential negative repercussions that may emerge from implementing improper technological solutions if they put a systematic technique into place for evaluating technology. This can be accomplished by implementing a systematic methodology for analysing technology. In the context of the ICT department, the relevance of regulatory changes on decision-making is an essential feature that must be addressed. This is especially true in data confidentiality, cybersecurity, and law adherence. The enforcement of the POPIA and analogous rules on a global scale have required organisations to enhance their data protection measures. This is because these policies are designed to protect personal information. According to Salmaso (2021) research findings, organisations that made regulatory compliance a top priority and included it in their decision-making methods displayed improved data privacy practices. The statement gives the impression that organisations that proactively adopt regulatory compliance can effectively assure data privacy protection through decision-making processes.

In addition, regulatory demands, such as those concerning cybersecurity procedures and industry-specific rules, have affected the installation of certain technologies and the decision-making processes involved in their use. The research carried out by Cremer *et al.* (2022) sheds light on the significance of regulatory compliance frameworks in their ability to influence decisions pertaining to IT security infrastructure. Adherence to these frameworks ensures that businesses satisfy the necessary security requirements, lowering the risk of potential dangers and improving decision-making regarding cybersecurity.

How do you plan to address potential concerns or resistance from staff regarding adopting an AI-enabled decision support system for decision-making?

The potential of AI to improve decision-making processes within organisations has received significant attention in recent times. Implementing decision support systems empowered by artificial intelligence exhibits the potential for enhanced efficacy and precision. The implementation of said systems within the ICT department may face opposition and apprehension from personnel (Lukyanenko, Maass, and Storey, 2022; Tiwari (2023).

Empirical research has revealed that ICT personnel have raised several noteworthy issues. According to Tiwari's (2023) findings, employees' apprehension of losing their jobs is a significant concern. A general apprehension exists that decision support systems empowered by artificial intelligence may obviate the necessity of human involvement or supplant their occupational functions within the enterprise. The apprehension expressed by individuals is based on the notion that AI can completely replace human decision-making, as posited by Malik, Tripathi, Kar, and Gupta (2021). These concerns indicate the apprehensions arising from technological progress and its potential implications for employment stability. Lockey, Gillespie, Holm, and Someh (2021) have identified a prevalent concern among ICT staff regarding the need for more trust in AI-enabled decision support systems. The precision, dependability, and ethical ramifications of AI algorithms are being scrutinized by personnel. Lukyanenko, Maass, and Storey (2022) have expressed apprehension regarding the exclusive dependence on machine-generated recommendations for making crucial decisions. The presence of trust is a pivotal element in the efficacious implementation of AI systems. At the same time, its dearth can hinder the reception and utilisation of such systems. Adopting AI-enabled decision support systems gives rise to a central theme of resistance to change. According to Malik *et al.* (2021), the implementation of AI in the workplace is met with resistance from employees who are hesitant to adapt to new work processes and skill requirements. The individuals' primary concerns are their capacity to adjust, assimilate novel technologies, and attain essential competencies. Resistance can impede an organisation's successful implementation and efficacy of artificial intelligence (AI) systems.

Additionally, the ICT personnel have raised apprehensions regarding the perceived relinquishment of authority over decision-making procedures while depending on AI-powered systems (Kelly, Kaye, & Oviedo-Trespalacios, 2022). There is a concern among experts that artificial intelligence (AI) may fail to consider crucial contextual elements or introduce partiality and inaccuracies that would be identified and corrected by human beings. As stated by Malik *et al.*, (2021), the resistance towards adopting AI is generated by the perceived loss of control. Personnel exhibit prudence in delegating decision-making jurisdiction to artificial intelligence systems without contemplating contextual subtleties. Adopting AI is influenced by organisational factors, which can significantly impact staff concerns and resistance, as noted by Tiwari (2023). The successful implementation of AI-enabled decision support systems can be impeded by staff apprehensions, often exacerbated by a lack of supportive organisational culture and insufficient leadership engagement (Malik *et al.*, 2021; Tiwari, 2023). Organisational leaders must cultivate a conducive environment that effectively attends to staff members' concerns and encourages a favourable disposition towards integrating artificial intelligence.

What challenges do decision makers face when they make decisions?

The significance of decision-making in the ICT department is crucial for achieving organisational success, as it directly impacts the management and utilisation of technological resources (Hilary *et al.*, 2023). Despite this, decision-makers face many obstacles that may hinder their capacity to render efficient operational decisions. Recent studies have illuminated various crucial obstacles that decision-makers in ICT encounter. Primarily, the swift advancement of technology and innovation poses a considerable challenge. Gupta, Ambashtha, and Kumar (2022) assert that decision-makers face a formidable challenge in keeping up with the latest technological advancements, which can result in challenges when identifying the most appropriate solutions for their respective organisations. The dynamic technological environment intensifies the challenge, which demands continuous education and flexibility.

Furthermore, the decision-making process within IT teams is significantly impacted by cybersecurity considerations and data privacy safeguarding. Triplett (2023) emphasised that individuals responsible for making decisions must adeptly navigate the complex network of cybersecurity threats and regulatory obligations. Inadequate addressing of these concerns can result in significant consequences for the organisation, such as compromising sensitive data, damaging reputation, and incurring financial losses. As a result, decision-makers must possess a comprehensive comprehension of the dynamic cybersecurity environment and integrate resilient security protocols into their decision-making procedures in a proactive manner. Triplett (2023) emphasises the significance of efficient collaboration with diverse stakeholders, such as top-level managers, departmental leaders, and external suppliers, to synchronise IT choices with the organisation's objectives. Effective coordination requires decision-makers to possess adept communication and negotiation abilities. Through proficient stakeholder engagement, decision-makers can ensure that their IT decisions are congruent with the wider strategic goals of the organisation, thereby promoting harmonious collaboration and synergy among various departments.

In summary, the process of decision-making within the IT teams is intricate. It involves multiple aspects that have a substantial impact on the success of an organisation. Decision-makers in this field encounter significant challenges, including the swift advancement of technology, cybersecurity risks, and the need for effective stakeholder coordination. These areas are particularly crucial and demand careful attention. Identifying these obstacles and formulating tactics to surmount them is crucial for decision-makers to render knowledgeable and efficacious operational judgements in the constantly evolving realm of information and communication technology.

As delineated in Chapter Three, the themes emerged from the research objectives and the semi-structured interviews with participants, resulting in the emergence of combined themes. These themes encompassed the interconnected ideas explored in the research revealing aspects that were investigated. By combining research objectives and participant perspectives these themes provided an understanding of the complexities within the ICT department. Moreover the convergence of these themes emphasised how various factors interacted with each other highlighting the relationships and dynamics observed in the case institution. By analysing insights and aligning them with the main research goals the study revealed a diverse range of findings that offered valuable perspectives and insights on the subject matter.

***Theme 1*: Decision-Making elements and their effects**

The analysis discusses the decision-making elements and their profound impacts on the operations of the ICT department at the university. The interviews explored the pivotal role that various decision-making elements play in shaping effective choices within the ICT department. Some of these elements include organisational culture, stakeholders, accurate information, risk assessment, technical documentation, users' needs and requirements. The organisational culture was revealed to be a defining factor in the decision-making landscape of the ICT department.

> *Participant 1's testimony elucidated the critical role of organisational culture in shaping decision-making strategies. With a commitment to resolving incidents, Participant 1 asserted, "I drive through the processes until resolution... I create task teams to get all*

the technical people involved." This proactive and collaborative approach stands as a testament to the pervasive influence of the department's organisational culture. Furthermore, the Participant 8's insights echoed this sentiment, underscoring the significance of a culture that fosters collective problem-solving.

Participant 4 emphasised that

> *"system changes require input from various stakeholders... this culture ensures that decisions are not isolated but rather integrated with broader organisational objectives."*

This collaborative ethos ensures that decisions transcend individual departments, promoting a holistic approach that aligns with overarching goals. Participant 7's perspective further emphasised the role of culture in promoting knowledge sharing and innovation. Participant 5 highlighted that

> *"a culture of continuous learning and information exchange facilitates the identification of novel solutions."*

This speaks to the empowering nature of an organisational culture that values knowledge dissemination, enabling decision-makers to tap into a reservoir of insights from diverse sources. In essence, the organisational culture acts as the bedrock upon which the decision-making landscape is built. Its influence permeates decision-making processes, impacting the way challenges are approached, solutions are crafted, and stakeholders are engaged. The culture's emphasis on collaboration, open communication, and knowledge sharing creates an environment in which decision-makers can harness collective intelligence, driving operational decisions that are informed, comprehensive, and aligned with the organisational vision.

Participant 2 highlighted the indispensability of real-time network status data, stating,

> *"Access to accurate network information empowers us to prioritise decisions during network incidents effectively." Echoing this sentiment, Participant 7 emphasised the role of comprehensive technical documentation, noting that "informed decisions hinge on the availability of up-to-date technical documentation."*

Participant 5 underscored the importance of evaluating risks and potential consequences, stating, *"Each decision should undergo meticulous risk assessment to forestall unintended disruptions."*

The Participant 1 added,

"Comprehensive impact analysis is a cornerstone; decisions must be made cognisant of their ripple effects on the organisation."

Participant 10 emphasised adherence to organisational policies, stating,

"Our decisions must align with established protocols and standards, ensuring congruence with our strategic direction."

These policies serve as guiding principles, especially in situations requiring swift action, underscoring the need for decisions that are both effective and compliant.

As revealed by Participant 2, flexibility emerged as a critical attribute in decision-making within the swiftly evolving technological landscape. Participant 2 underscored,

"Rapid adaptation is essential; decisions need to accommodate dynamic shifts in network configurations and emerging vulnerabilities."

This sentiment is reinforced by Participant 6, who highlighted the need for agility in responding to multifaceted technical exigencies. Their perspectives emphasised those decisions characterised by adaptability are inherently poised to address emergent challenges effectively.

Intriguingly, Participant 4’s viewpoint brought to light the significance of user-centric decision-making. Participant 4 emphasised,

"Decisions resonate most when they reflect the end-users' needs and challenges; a user-centric approach is fundamental to crafting solutions that harmonise with user experiences."

This sentiment reverberated through the interviews with Participant 7 and Participant 10, who both concurred that decisions must align with user expectations, offering seamless experiences and augmenting operational efficiency. A recurrent theme underscoring decision-making efficacy is resource optimisation. Participant 8 expounded, *"Balancing resource allocation is a delicate choreography; decisions must harness available resources judiciously to ensure efficient solutions without overburdening the system."*

This sentiment is echoed by Participant 5, who added,

"Resource allocation decisions cascade through operations; prudent allocation influences service levels and operational continuity."

Both perspectives underlined that resource allocation decisions are pivotal in maximizing efficiency and minimising disruptions. Unveiling the growing significance of data-driven decision-making, Participant 10 emphasised the role of data in bolstering decision-making accuracy. Participant 10 asserted,

"Leveraging data-driven insights is transformative; decisions founded on comprehensive data analytics are inherently equipped to optimise outcomes."

This perspective resonated with Participant 3’s viewpoint, who underscored the use of historical data to anticipate potential issues. Evidently, data-derived insights contribute to prescient and well-grounded decisions. A recurrent theme that surfaced across stakeholder interviews is the power of collaborative decision-making. Participant 6 accentuated,

"Pooling collective expertise optimises decisions; cross-functional collaboration ensures comprehensive perspectives, thereby refining choices."

Participant 1 concurred, elaborating on the formation of task teams that unite diverse technical competencies to expedite resolution. Collaborative decision-making emerges as an avenue to harness the collective wisdom of the team.

This in depth exploration into the aspects of decision-making and their complex consequences highlights the nature of operational decisions in the ICT department. By examining the viewpoints of stakeholders this analysis delves into the web of decision making uncovering the factors that contribute to making effective and well-rounded choices. The ICT department should utilise a comprehensive approach that incorporates various decision-making elements to ensure optimal outcomes and align with organisational goals. Firstly, understanding and adapting to the organisational culture is paramount, as it sets the tone for decision-making processes and the acceptance of technological changes. Stakeholder involvement is crucial, as their perspectives and needs must be considered to ensure solutions meet user requirements and expectations. Accurate information serves as the foundation for informed decision-making, enabling the ICT department to assess situations accurately and identify the most suitable courses of action. Conducting thorough risk assessments allows for the identification and mitigation of potential risks, safeguarding against adverse impacts on operations. Technical documentation provides essential guidelines and references, facilitating efficient problem-solving and knowledge transfer within the department. Moreover, prioritising users' needs and requirements ensures that ICT solutions are user-friendly and effective in addressing real-world challenges. Time constraints necessitate swift decision-making, emphasising the importance of efficiency and prioritization. Finally, having access to adequate resources, including budget, personnel, and technology, is essential to implement decisions effectively and achieve desired outcomes. Participants insight demonstrate that by leveraging decision-making elements, the ICT department can navigate complex challenges and drive innovation while delivering value to the organisation.

***Theme* 2: Operational Decision-Making Processes**

In this section, the focus shifts to the operational decision-making processes within the ICT department of the university. Delving into the processes and systematic frameworks that guide decision-making, this segment explored the behind-the-scenes activities that culminate in effective choices.

Operational decisions within the ICT department are not haphazard, but rather grounded in a systematic framework that ensures strategic alignment. As highlighted by the Participant 1,

> *"Our decision-making process is methodical; it adheres to established protocols that help us navigate through complexity."*

This sentiment is corroborated by Participant 10, who emphasised the adherence to a structured approach that optimises choices. Such systematic frameworks are critical to prevent ad-hoc decisions and ensure consistency.

A pivotal phase within operational decision-making involves the collection and analysis of relevant data. Participant 6 explained,

> *"Data collection arms us with insights; we gather technical data, user feedback, and performance metrics to comprehensively understand the situation."*

This perspective shows the importance of empirical insights as a foundation for informed choices. Additionally, Participant 8 mentioned the utilisation of testing data to scrutinise potential solutions which showed the careful analysis of data-guided decisions towards optimal outcomes. Operational decisions rarely present a single path. Rather, they involve evaluating various alternatives to determine the most suitable course of action. Participant 4 stressed, "Assessing alternatives is crucial; different solutions can have varying impacts on user experiences and system performance." Participant 10 echoed this sentiment, emphasising the need to weigh pros and cons before making decisions. Such a comprehensive evaluation of alternatives serves to mitigate risks and optimise outcomes.

Stakeholders' perspectives play an integral role in shaping operational decisions. Participant 3 revealed,

> *"Stakeholder involvement is vital; their insights provide a broader context that enriches decision-making."*

This collaborative approach is reinforced by the Participant 8, who highlighted the significance of gathering inputs from technicians and users alike. By incorporating diverse viewpoints, decisions can be holistically informed and attuned to the collective needs of the ICT ecosystem. Operational decisions are fraught with uncertainties, and prudent decision-making necessitates the identification and mitigation of potential risks. Participant 1 mentioned,

> *"Risk assessment is inherent in our process; we evaluate potential consequences and devise contingency plans."*

This approach is echoed by Participant 10, who emphasised the need to anticipate challenges and devise fallback strategies. Risk-conscious decision-making ensures preparedness and minimises disruptions.

Operational decisions are not just isolated actions but are embedded within the overarching goals of the organisation. Participant 5 emphasised,

> *"Our decisions must align with the organisation's vision; this alignment ensures that our choices contribute to the larger strategic trajectory."*

Participant 4 brought the importance of synchronisation with broader objectives, adding that user-centric decisions often resonate with organisational goals. Such alignment ensures that operational decisions reinforce the organisational fabric. The participants noted that the

Operational Decision-Making Processes within the ICT department are systematic; however, they are characterised by siloed approaches, with each unit operating independently and without proper coordination or communication with other units. AI can effectively address the siloed operational decision-making processes within the ICT department by integrating data sources, facilitating predictive analytics for proactive decision-making, enabling collaborative decision-making through real-time communication tools, automating workflows to streamline processes, and promoting knowledge sharing across units.

Theme 3: Challenges in Operational Decision-Making

The operational decisions undertaken within the ICT department are not devoid of challenges. This section delves into the specific hurdles and complexities that decision-makers encounter as they navigate the dynamic landscape of information and technology. By identifying and understanding these challenges, the ICT department can devise strategies to overcome them and enhance the effectiveness of its decision-making processes. One of these challenges relates to optimal resource allocation is essential for effective operational decisions. However, budget constraints can limit the scope of possibilities. Participant 10 acknowledged,

> *"Allocating resources strategically within budget limitations is akin to solving a puzzle. We need to maximize the value derived from each resource."*

The challenge lies in ensuring that resource allocation aligns with both immediate needs and long-term goals, even when financial boundaries are present. One of the foremost challenges faced by decision-makers in the ICT department is the intricate nature of modern technology. Participant 3 highlighted,

> *"The ever-evolving technological landscape presents a complex puzzle. Staying abreast of emerging trends and ensuring seamless integration requires constant vigilance."*

This challenge is echoed by the Participant 5, who emphasised that the diversity and rapid evolution of technology can lead to decision paralysis. Thus, decision-makers must continually update their knowledge to make informed choices. Participant 7 pointed to the inherent uncertainty in technology-related decisions, noting,

> *"Predicting the outcome of a decision in a rapidly changing environment is a challenge. Unforeseen risks can emerge, impacting the entire system."*

Participant 9 said the importance of risk assessment and mitigation strategies, emphasising that decisions must balance innovation with risk management. Decision-makers are tasked with charting a course that embraces innovation while minimising potential disruptions. This is a time-consuming process as depicted in Table 4.1 below.

Table 4.1 Traditional Business Process Automation

User Requests	Business Manager Responses
Request service by email ⟹	⟸ Ask for more information
Expand on the email ⟹	⟸ Request detailed information e.g., process owners, stakeholders, budget, sponsors, approval.
Walk-in for verbal explanation ⟹	⟸ Clarity on start, stop, continue
No current document process ⟹	⟸ Require documentation?
Compile paperwork ⟹	⟸ Change agents and roles?
Amend paperwork ⟹	⟸ Involve which departments?

Table 4.1 shows the traditional request for process automation is that users typically submit requests through manual channels, such as filling out forms or sending emails, to initiate the automation of specific tasks or processes. After back-and-forth communication and clarification, these requests are then reviewed and processed by the Business Process Architecture who determines the feasibility and priority of each automation request. Once approved, the automation process is implemented by the ICT team or relevant personnel. The collaborative nature of operational decisions often gives rise to collaboration challenges. Participant 6 pointed out,

> *"Different departments may have conflicting priorities or communication breakdowns. Achieving alignment requires clear communication and shared objectives."*

Participant 9 added that diverse viewpoints can lead to complexities, making consensus-building a multifaceted endeavour. Overcoming these challenges necessitates effective communication, mutual respect, and a shared understanding of the larger organisational vision. Operational decisions frequently operate under time constraints, demanding swift yet informed choices. Participant 1 acknowledges the urgency, stating, *"Time sensitivity can lead to decisions made in haste, potentially overlooking critical factors."*

This sentiment is echoed by Participant 2, who noted that balancing accuracy and timeliness is a perpetual challenge. Decisions made under pressure require careful consideration to avoid unintended consequences. The era of abundant information poses its own challenges, often leading to decision paralysis. Participant 7 remarked,

"Having access to copious data is both a boon and a bane. The challenge is sifting through data to extract actionable insights."

The Participant 10 concurred that information overload can lead to delayed decisions as decision-makers grapple with information analysis. Striking a balance between data utilisation and decision expediency is a perpetual challenge. Operational decisions necessitate aligning immediate needs with long-term organisational goals. Participant 9 observed,

"The challenge lies in not sacrificing long-term objectives for short-term gains."

The Participant 10 added that this requires a holistic perspective that evaluates how each decision contributes to the overarching vision. Achieving this balance demands strategic acumen and a deep understanding of the organisation's trajectory. AI can enhance operational decision-making in the ICT department by breaking down data silos, predicting potential issues, fostering collaboration, automating tasks and sharing insights. This can ensure that decisions are made collectively and align with departmental goals, leading to more efficient and agile responses to challenges and opportunities.

***Theme 4*: Integration of AI in Decision-Support**

As the landscape of information and technology evolves, so too does the potential for integrating AI into decision-support systems. The ICT department's decision-making procedures might be improved with the help of AI.

"AI systems can analyse vast datasets, extract patterns, and offer insights that humans might overlook," Participant 2 observed. Participant 5, who emphasised how AI-enabled technologies may automate data processing so that decision-makers can concentrate on strategic analysis, supports this idea. By automating data-intensive jobs, the incorporation of AI may increase the effectiveness of decision-makers.

Participant 10 explained,

> *"AI can identify trends, predict potential disruptions, and recommend proactive measures." By leveraging historical data, AI can generate insights that aid decision-makers in anticipating challenges and making informed choices. This empowers decision-makers to address issues pre-emptively, reducing the likelihood of operational disruptions. Participant 10 emphasises that AI's ability to assess risk and provide probabilistic outcomes can transform decision-making. "AI models can simulate scenarios, quantifying potential risks and their impact" Participant 9 said.*

Such simulations enable decision-makers to evaluate multiple alternatives and assess the associated risks before committing to a course of action. This capability equips decision-makers with a broader understanding of potential outcomes, facilitating risk-informed decisions.

AI's adaptability extends to generating personalised recommendations tailored to specific contexts. Participant 8 underscored, "AI systems can understand individual preferences and organisational goals, delivering recommendations that align with both." By considering individual decision-makers' preferences and broader organisational objectives, AI can offer customized suggestions that guide decision-makers toward optimal choices.

Traditional network management in the ICT department at the selected case university involves manually monitoring and configuring the network infrastructure to ensure its smooth operation. Network administrators are responsible for tasks such as device configuration, monitoring network traffic, troubleshooting issues, and ensuring security protocols are in place. However, as the university's IT infrastructure grows in complexity and size, the traditional approach may face challenges in terms of scalability, efficiency, and timely responses to potential network issues. AI can significantly improve network management in the ICT department by introducing automation and intelligence.

While AI presents significant potential, integration is not without its challenges. Participant 1 acknowledged, *"Ensuring the accuracy and reliability of AI-generated insights is paramount." AI models are only as good as the data they are trained on, and biases in data can lead to skewed recommendations.* Participant 3 adds that ethical concerns, such as algorithmic transparency and accountability must be addressed to ensure AI's responsible integration. Participant 6 highlighted the symbiotic potential of human-AI collaboration. *"AI can enhance decision-making, but human intuition and domain expertise remain invaluable,"* Participant 6 stated. AI's role is not to replace decision-makers, but to augment their capabilities by providing data-driven insights and accelerating data processing. Decisions made because of this teamwork may be more intelligent, effective and contextually aware.

The operational choices made by the ICT department may be transformed by the incorporation of AI into decision-support systems. AI can completely change how decisions are made, from data-driven insights and predictive analytics to individualised suggestions. However, difficulties with accuracy, prejudice and ethical issues highlight the necessity for cautious implementation and ongoing supervision. The ICT department can exploit AI's ability to improve decision-makers' capacities and propel technical growth inside the university's ecosystem by encouraging a collaborative interaction between staff and AI system.

***Theme 5*: Alignment with Organisational Goals**

Beyond the immediate operational advantages, the integration of AI-enabled decision-support systems inside the ICT department have the potential to serve the university's larger interests and goals. In-depth discussion of how the use of AI fits with the university's organisational goals and vision is provided in this section. The university's quest of excellence and innovation is perfectly complemented using AI-enabled decision-support technologies. Participant 10 emphasised that

> *"AI's capabilities can elevate the efficiency and effectiveness of decision-making, resonating with our commitment to deliver high-quality services and solutions."*

By harnessing AI to streamline decision processes, the ICT department can better support the university's overarching mission to excel in education, research, and service. Participant 2 underscores AI's role in resource optimisation, a key organisational priority.

"AI's ability to analyse data and provide insights in real time can lead to resource allocation that is both efficient and targeted," noted Participant 2. This translates to optimised allocation of budget, personnel, and technological resources, ensuring the university operates at its most cost-effective and impactful levels. Participant 9 underscores AI's contribution to strategic planning.

"AI's predictive capabilities can aid in foreseeing trends and potential challenges, allowing the university to proactively strategise," explained the Participant 9. By incorporating AI-generated insights into strategic discussions, the university can make more informed decisions that align

with long-term objectives, adapt to evolving technological landscapes, and capitalise on emerging opportunities. The integration of AI reflects the university's aspiration to be at the forefront of technological innovation. Participant 8 mentioned that

> *"AI's implementation signifies our commitment to embracing cutting-edge solutions that position us as leaders in the ever-evolving digital landscape."*

By adopting AI-enabled decision-support systems, the university demonstrates its dedication to driving innovation and leveraging technology to advance its core mission.

Participant 5 notes that AI's integration can foster a data-driven decision culture across the university. *"AI's reliance on data and evidence can cultivate a culture that values informed choices,"* stated the Participant 5. As AI-generated insights become integral to decision-making processes, the university's stakeholders can become more comfortable with leveraging data to drive strategies, thereby aligning with the institution's goals of evidence-based management. While AI integration presents opportunities, the alignment with organisational goals must be carefully navigated. Participant 1 emphasises the need for ethical considerations and transparency.

"Ensuring that AI-generated decisions are explainable and trustworthy is crucial to maintaining the university's commitment to integrity and accountability," noted Participant 1. Alignment with organisational goals necessitates AI solutions that uphold ethical standards.

The integration of AI-enabled decision-support systems within the ICT department resonates with the broader organisational goals of the university. By enhancing efficiency, resource optimisation, strategic planning, innovation, and data-driven decision-making, AI can align seamlessly with the university's pursuit of excellence and technological leadership. However, this alignment must be underpinned by ethical considerations and transparency to ensure that AI's benefits are realised in ways that uphold the university's values and commitments.

***Theme 6*: Implications for AI-Enabled Decision Support System**

The journey of exploration and analysis undertaken by the researcher leads to a pivotal juncture: uncovering the profound implications of integrating AI into decision-support systems within academic environments. This section delves into the multifaceted implications that arise from the adoption of AI, shedding light on its potential to reshape decision-making processes, institutional dynamics, and the future of academic operations. One of the most profound implications of integrating AI within decision-support systems is the transformation of complexity into clarity. Participant 6 highlighted that AI's analytical prowess simplifies intricate data sets, enabling decision-makers to swiftly discern patterns and trends. This capability streamlines decision-making processes, fostering agility in addressing challenges and seizing opportunities. As articulated by Participant 2, AI-driven decision-support systems contribute significantly to precision in decision-making. *"The amalgamation of historical data, real-time insights, and predictive analysis bolsters the accuracy of decisions,"* noted Participant 2. Participant 10 emphasised, "AI's ability to optimise resource allocation, whether in terms of human resources, financial allocations, or technological assets, magnifies operational efficiency." This heightened precision translates into well-informed choices that align with organisational goals.

Interestingly, in the ICT department the current traditional incident management process specifically refers to the established procedures and protocols followed for handling and resolving IT-related incidents. This process involves a series of steps that the ICT team undertakes when responding to incidents reported by users. The ICT team is responsible for logging and categorising the incidents, assessing their impact and urgency, and assigning them to the appropriate ICT staff for investigation and resolution. Throughout the process, communication with users and stakeholders is vital to keep them informed about the incident's progress and resolution status. Once the incident is resolved, the ticket is closed. Although the traditional process has been effective in the case of the university, it can benefit from automation and AI-driven solutions to enhance efficiency, reduce response times, and improve overall incident management in the ICT department.

The integration of AI compels academic institutions to embrace a culture driven by data and evidence. Participant 8 elaborated,

> *"AI's reliance on data nurtures a culture of data-driven decision-making, thereby fostering a more informed, efficient, and accountable institution."*

The resonance of AI-powered insights with institutional goals propels the transformation from intuition-based decisions to those firmly grounded in empirical evidence. Institutions of higher learning thrive on strategic planning and innovation. Participant 9 highlighted, "AI's ability to anticipate trends and challenges empowers institutions to shape visionary strategies and innovative solutions." This anticipatory prowess positions the academic institution as a proactive leader in adapting to change, aligning seamlessly with its quest for advancement.

While AI presents transformative possibilities, ethical and privacy considerations demand careful attention. Participant 1 underscored,

> *"The integration of AI necessitates robust protocols to ensure data privacy, algorithmic transparency, and ethical decision-making."*

The implications of AI extend beyond efficacy to encompass ethical frameworks that align with the institution's values. As AI assumes a role in decision-support systems, a shift in human roles becomes evident. The researcher recognises that AI's integration redefines human responsibilities, transforming decision-makers into orchestrators of AI-generated insights. This shift, while altering job profiles, aligns with the university's adaptability ethos, preparing stakeholders for the evolving landscape. By leveraging AIDSS capabilities, the case institution can unlock new efficiencies, improve service quality, and deliver better outcomes for their students and staff.

4.3 Interpretation

The results unearthed through the exploration of decision-making elements within the ICT department align with previous research that highlights the significance of decision-making in organisational effectiveness. Scholars such as Mintzberg (1976) and Simon (1977) underscore the intricate interplay between decision-making processes and organisational outcomes. Participant 6’s assertion that AI simplifies complex data resonates with the sentiments of Wang and Strong (1996), who emphasise AI's role in transforming voluminous data into actionable insights.

The assertion made by the Participant 2 regarding the enhanced decision-making precision facilitated by AI mirrors the sentiment expressed by Barwise and Farley (2005) in their seminal work on data-driven decision-making. Barwise and Farley underline the shift from intuition-based decision-making to a data-centric approach, emphasising the pivotal role of data analysis in guiding decisions. AI's integration aligns seamlessly with the tenets of Big Data analytics, exemplifying the evolution of decision-making paradigms. Laney's (2001) articulation of Big Data's potential in facilitating real-time data assimilation and analysis underscores the significance of AI-powered algorithms in enhancing decision-making accuracy. The fusion of AI and Big Data principles synergistically elevates decision-making precision. AI's capacity to rapidly process vast datasets, discern patterns and predict outcomes reflects the essence of data-driven decision-making. This confluence validates the finding that AI enhances decision-making precision by anchoring decisions in robust data analysis.

Participant 10's insight into resource optimisation resonates profoundly with Davenport's (1993) seminal work on process optimisation. Davenport underscores the importance of strategic resource allocation to streamline operations, foster efficiency, and drive organisational success. In parallel, AI's prowess in optimising resource allocation dovetails with the notion of "smart systems" championed by Brynjolfsson and McAfee (2011). These systems leverage technology to intelligently allocate resources, minimising wastage and maximising utility. The alignment between Participant 10's observation and established principles of efficiency accentuates the transformative potential of AI. By automating resource allocation decisions based on real-time data insights, AI empowers organisations to achieve greater operational efficiency. This correspondence between interview findings and literature substantiates AI's capacity to enhance operational efficacy.

The Participant 8’s acknowledgment of AI's role in fostering a data-driven decision culture resonates with the discourse on evidence-based management advocated by Pfeffer and Sutton (2006). Mahrinasari *et al.* (2021) emphasise the importance of informed decisions rooted in empirical evidence, advocating for a cultural shift towards data-driven practices. In parallel, AI's infusion into decision-making aligns with the transformative potential of data-driven cultures, as underscored by Bryson *et al.* (2011). The congruity between the Participant 7’s insight and established literature underscores the multi-dimensional impact of AI on organisational culture. AI not only enhances decision-making but also fosters a cultural shift towards data-centric practices. This alignment validates the finding that AI's influence transcends immediate operational improvements, extending its reach to shape the very fabric of institutional culture.

The perspective shared by the Participant 9 concerning AI's role in strategic planning and innovation closely aligns with the concept of strategic foresight as proposed by Teece (2007). Strategic foresight involves anticipating future trends and disruptions to inform proactive decision-making. The correlation between AI and strategic planning resonates with studies that emphasise AI's ability to predict trends and enable organisations to take pre-emptive measures (Bughin *et al.*, 2018). This alignment validates the interview's finding that AI integration extends into shaping visionary strategies that position organisations for future success.

The ethical considerations highlighted by Participant 1 find resonance in the ethical AI frameworks advocated by Floridi and Cowls (2021). These frameworks emphasise the need for transparency, accountability, and data privacy in AI systems. The acknowledgment of the importance of transparent algorithms and data protection aligns seamlessly with discussions on responsible AI implementation and governance (Jobin *et al.*, 2019). The congruity between the interview findings and ethical AI literature underscores the significance of embedding ethical considerations in AI-enabled decision-support systems to ensure responsible and trustworthy deployment.

The researcher's insight into paradigm shifts in human roles due to AI aligns with the concept of the "augmented human" proposed by Brynjolfsson and McAfee (2011). The augmented human framework envisions humans working alongside AI systems to enhance productivity and decision-making. This transformation of human roles resonates with studies exploring AI's impact on the workforce, where augmentation rather than replacement emerges as a key theme (Manyika *et al.*, 2017). The coherence between the interview findings and established literature validates the notion that AI reshapes the dynamics of human responsibilities within organisational contexts.

Three overarching themes surface from the data collected through interviews:

The Requirement for Automating Business Processes (BPA): To improve efficiency minimise errors and make the best use of resources it is crucial to implement Business Process Automation within the ICT department. This can involve automating tasks and streamlining workflows.

The Necessity for Proactive IT Maintenance: It is essential to prioritise IT preventative maintenance as it plays a crucial role in minimising downtime avoiding potential problems and ensuring the consistent and reliable performance of IT systems. By addressing any issues before they worsen the university can greatly improve continuity.

The Need for Predictive Analysis Of Network: This arises from the goal of anticipating problems, identifying vulnerabilities and ensuring the possible performance. Using predictive analytics, the university can take steps to improve network reliability, minimise disruptions and make informed decisions for managing and optimising their networks.

The reflections on future directions presented in the study harmonise with discussions on the evolving landscape of AI, as explored by Varshney and Jain (2017). The call for interdisciplinary collaboration and continual AI evolution aligns with literature advocating for agile and flexible approaches in AI implementation (Brynjolfsson & McAfee, 2011). This alignment between the interview findings and future AI directions lends credibility to the implications put forth in the research. It substantiates the notion that AI's potential goes beyond the present and offers a dynamic trajectory for organisational growth and innovation.

4.4 Chapter Summary

This chapter presented the research findings in line with the qualitative data collection methods. Participants' statements were cited and quoted verbatim and in some instances the researcher summarised their viewpoints. The next chapter discusses the development of the artefact.

CHAPTER 5: ARTEFACT DEVELOPMENT

5.1 Introduction

The preceding chapter focused on data analysis utilising data gathered through interviews. The qualitative data gathered through interviews was analysed using thematic analysis to identify patterns and themes in the data. The data provided problem identification as per DSR protocol. It provided insight into the users' needs, preferences, and challenges to develop the proposed AIDSS that can support operational decision making in the ICT department of the case university. This chapter discusses the processes and steps that were followed in developing the artefact. Hevner et al., (2008) assert that according to the fundamental principle of Design Science Research, by constructing and employing the artefact in context, knowledge of the solution and comprehension of the design problem are attained. These researcher further argue that the artefact brings about a reality for individuals who may potentially utilise it (Hevner et al., 2008). The outcome of Design Science Research is an Information Systems artefact designed to tackle an issue within the organisation. This study involves the design and development of an artefact; therefore, the DSR conceptual framework was used as depicted in Figure 1.7. This process can help to create more effective and efficient solutions to real-world problems specifically in the ICT department of the case university.

5.2 Five steps for conducting Design Science Research

Upon careful consideration of the available approaches for doing Design Science research, this study utiised the technique proposed by Kuechler and Vaishnavi (2008). The following five guidelines were adopted:

5.2.1 Activity 1: Problem Awareness

The operating of information systems in separated silos, which generate significant volumes of complex data that pose challenges for traditional data processing, can explain poor decision-making observed at the case institution. Semi-structured interviews conducted in the ICT department aimed to identify and verify the problem. Activity One discusses Problems. The results of semi-structured interviews are detailed here. The reason for using structured interviews was to accurately identify and delve into the issue mentioned in the research problem statement in Chapter One. These interviews were designed to uncover the nuances and complexities surrounding the problem, helping the researcher fully understand its intricacies. Additionally, through these interviews the researcher aimed to build an argument for implementing a solution tailored to the university's context. By gathering perspectives from individuals these interviews provided insights that emphasised the importance of addressing the highlighted issue within the university's environment.

Based on the insights gathered from the semi-structured interviews the researcher came to some conclusions that paved the way for actions. Firstly, it was clear that there is a need for an Artificial intelligence-enabled decision support system (AIDSS) to support operational decision making in the ICT department. The management team strongly believes that implementing AIDSS would be advantageous and help improve decision making. Additionally, the IT team has shown a willingness to embrace and use the AIDSS for their decision-making needs. The demand for AIDSS spans across areas such as automating business processes, managing IT assets, predicting trends, monitoring the network and handling incidents. These findings highlight the importance and potential benefits of introducing AIDSS into the case university.

5.2.2 Activity 2: Suggestion

Following the recognition of the problem inside the case university's ICT department, the subsequent step involves delineating the suggestion that is rooted in the identified problem. The proposed solution must be both attainable and viable. As detailed in Activity Two below, the aim of the proposed system is to improve operational decision-making in the case of university.The problem described in Activity One was addressed by creating the proposed prototype called AIDSS, which aimed to assist decision making in higher education institutions. Through developing this prototype, the objective was to offer a solution that would support decision making in education institutions specifically within the ICT department. The goal of this tool was to improve and simplify decision making processes in the ICT department as defined earlier in Chapter One, this would ultimately lead to effective decisions in the department. This approach aligned with the objective stated at the beginning of the project emphasising the importance of using technology to optimise decision making processes. As collated from Chapter Four, the following is a list of the three requirements that the university has outlined for the system:

- Business Process Automation (BPA).
- Preventative Maintenance.
- Predictive Analytics.

i) Business Process Automation (BPA)

The case university has many business processes that must be automated. Hence, the university wants to manage the requests for business process automation in a systematic way so that it can prioritise the requests and ensure that the most important ones are automated first. Furthermore, because of limited resources, the university relies solely on a Business Process Manager (BPM) for handling organisational process automation. Given this constraint, the university requires a tool that allows employees to submit requests for BPA. It is therefore proposed that the AIDSS makes use of a Chat functionality to capture the business process automation requests from the employees. Shown in Figure 5.1 below is the BPAChatBot architecture.

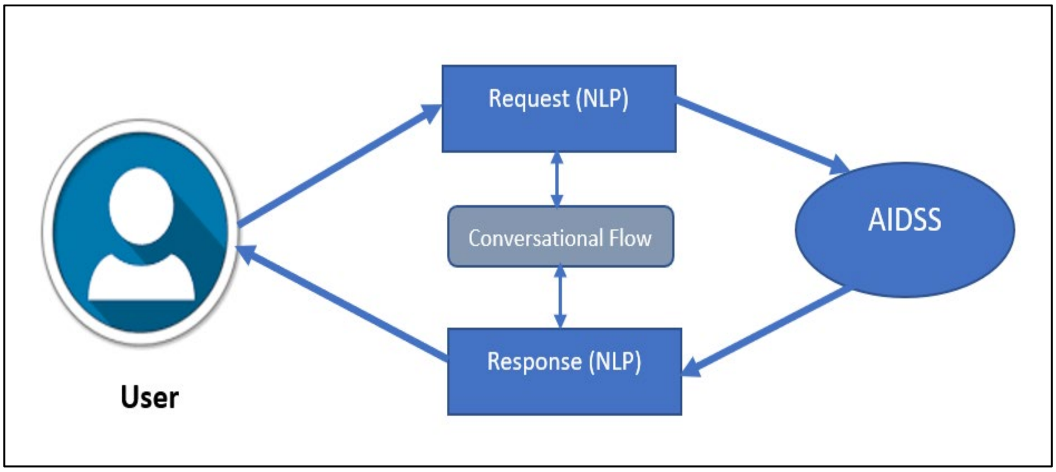


Figure 5.1 BPAChatBot Infrastructure

The development of a Chat system becomes crucial to effectively collect employee requests. AI powered chatbots rely on natural language processing (NLP) to analyse users' requests and identify keywords. This enables them to determine the response. Additionally, AI driven chatbots incorporate machine learning integration, which allows them to improve themselves by interacting with user data. The obtained data is then used as training material to expand their knowledge base resulting in more accurate and relevant answers. The BPAChatBot aims to alleviate the burden on the BPM by streamlining the request-capturing process. This can be a valuable tool for managing the requests for business process automation. By using the Chat functionality, the university can improve the efficiency and effectiveness of their automation projects.

ii) Preventative Maintenance

The ICT department maintains university computers that are used by employees. The department has a policy of conducting preventative maintenance on the computers every six months. This includes tasks such as cleaning the computers, updating the software, and replacing any faulty components. Therefore, the AIDSS is proposed to improve the efficiency of the IT Asset preventative maintenance process. The AIDSS can also be used to identify any potential problems with the computers. For example, the system can be used to monitor the computers for errors or performance issues. If the system detects any problems, it can generate a notification for the IT staff so that they can take corrective action. Depicted in Figure 5.2 below is the preventative maintenance infrastructure.

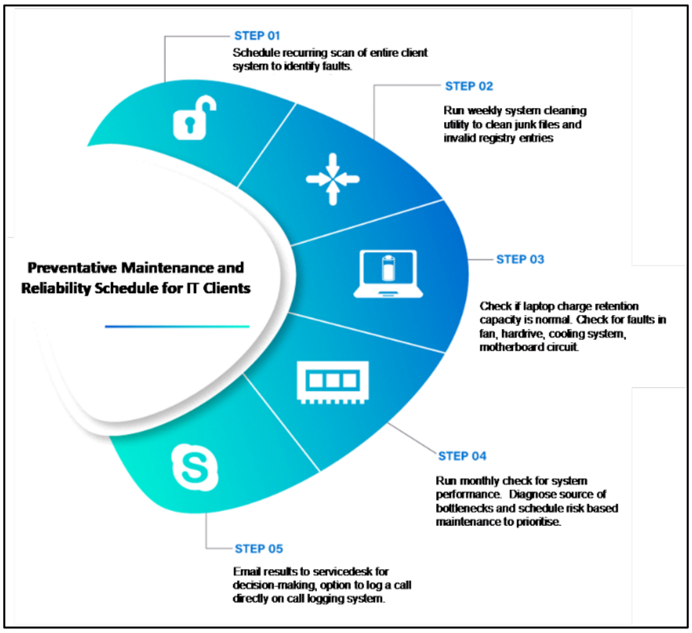


Figure 5.2 Preventative Maintenance Infrastructure

Using the AIDSS, the ICT department can improve the efficiency of its preventative maintenance process and reduce the risk of computer problems. This can save the department time and money, and it can help to ensure that the computers are always available for employees to use.

iii) Predictive Analytics

The university has a large and complex network that is used by employees. The company wants to use predictive analytics to monitor the network and identify potential problems before they occur. The company wants a predictive analytics tool to collect data on the network's performance. The data includes information such as the network's traffic patterns, the number of devices connected to the network, and the performance of the network's devices. In addition, the proposed AIDSS can use this data to build models that can predict future network problems. For example, the AIDSS might be able to predict that a particular device is likely to fail in the next 24 hours. Predictive analytics infrastructure for network monitoring is portrayed in Figure 5.3 below.

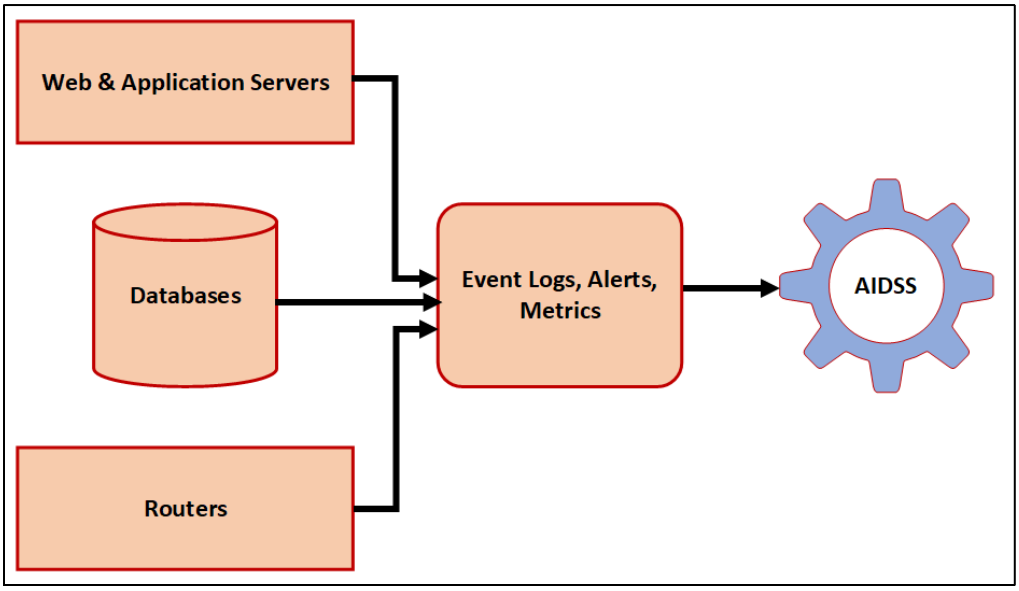


Figure 5.3 Predictive Analytics Infrastructure

Through using the AIDSS, the ICT department can identify and resolve network problems before they impact employees. This can help to improve the availability of the network and reduce the risk of downtime.

5.2.3 Activity 3: Develop the Artefact

The process of designing and developing an artefact is at the centre of the DSR methodology. During Activity Three, this project successfully created a prototype for an AI-enabled decision support system to support operational decision-making within the ICT department at the university. This portion outlines the design and development of the artieact as well as its fundamental features. The proposed AIDSS works by using intelligence techniques to analyse data, provide valuable recommendations and support decision makers in their tasks. Thereby harnessing the power of AI this system greatly improves the ICT department’s decision-making processes creating an environment where informed and strategic choices are made based on data driven insights. To address the identified problem and realise the proposed solution, the architectural design of the AIDSS that is enabled by artificial intelligence is essential. The design of the AIDSS architecture depicted below in Figure 5.4 will guarantee that the system is both strong and scalable, as well as specifically suited to handle the difficulties that the university confronts. The ICT department decision-makers will be provided with data-driven insights via the system, which will eventually contribute to the improvement of decision-making.

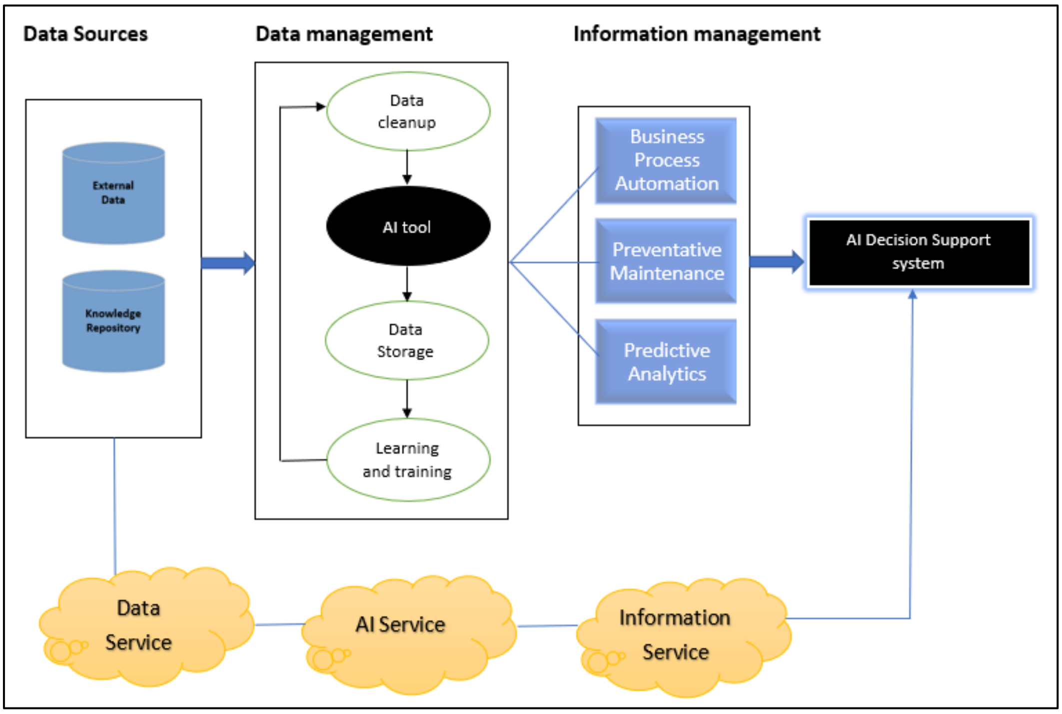


Figure 5.4 AIDSS Architecture

The integration of insights as depicted in the AIDSS architecture above is expected to improve the quality of decision making. These improvements will be achieved by using data sources, advanced AI algorithms and a reliable decision support engine working together to provide comprehensive and well-informed recommendations for better decision outcomes. The user interface and the system's alignment with the aims of the university will both contribute to the system's increased usability and effectiveness. As displayed in Figure 5.4 above, the AIDSS is composed of three main elements, the Data Service, AI Service and Information Service.

iv) Data Sources

External data and knowledge repository are the variables that reflect the IT event logs, alerts, prompts, that may be found inside computer systems in the case university. The AIDSS will consume this information to fill up its extensive database. Computer logs and events contain unstructured information, often consisting of human-readable English phrases that are recorded by various components within a computer system. These logs capture important activities, errors, and interactions occurring within the system. However, this information is not organised in a standardised way, making it challenging to extract insights directly. In the context of an AI-Driven Decision Support System (AIDSS), the system's role is to convert this unstructured data into structured and usable formats. It processes the raw log data, extracting relevant details and translating them into a structured form that can be easily understood and analysed. Once transformed, this data is loaded into the Decision Support System's (DSS) data store, where it can be efficiently queried, analysed, and utilised to provide informed decision-making support. Therefore, by integrating and analysing both internal and external data sources, the AIDSS can provide a comprehensive view of the IT environment's health, performance and potential issues. This holistic understanding can enable the IT team to make informed decisions.

v) Data Management

The AIDSS Data Management involves the organisation, processing, and storage of diverse data sources. This ensures that data, ranging from structured to unstructured formats, is collected, cleaned, transformed, and stored in a manner that allows the AIDSS to provide accurate insights and recommendations for effective decision-making.

- ***Data Cleanup***: describes the combination method through which disparate data sets form a cohesive whole. AIDSS harmonises data from internal systems, guaranteeing reliability and precision for sound decision-making.
- ***AI Tools:*** the AI algorithm indicates the foundational AI technologies that will analyse the combined dataset and draw conclusions. These include machine learning algorithms, natural language processing and data mining. The system will be able to recognise patterns, anticipate trends, and provide the best workable solutions thanks to these algorithms.
- ***Data Storage***: ensures the AI engine has access to all the information and queries pertaining to the tasks needed for the operation of the AIDSS. A knowledge base repository managed by the AI system stores these details.
- ***Model Teaching & Learning:*** during the training phase of the model, it learns from datasets by identifying patterns, relationships and trends in the given information. It utilises machine learning techniques and the model adjusts its parameters to improve prediction accuracy.

vi) Information Management

The information management section considers the interconnections and dependencies between services and databases. Databases, data warehouses, and Big Data repositories play crucial roles in handling, managing, and extracting insights from vast amounts of data. This is especially important because an AIDSS will involve components and data sources that work together to provide recommendations or insights. As a result of having dynamic dependency information the AIDSS can accurately access the data and services as they evolve allowing it to make informed decisions based on the most recent and relevant information. This understanding of dependencies enables the system to operate effectively, adapt to changes and offer decision support across scenarios. Ensuring the reliability and stability of computer systems is of paramount importance for the ICT department of the case university. Hence, to address the identified problem, the chat model for Business Process Automation (BPA), and the AI-driven fault detection models for laptops and servers have been developed as part of the AIDSS. These models are designed to assist decision-makers by automating the BPA request, and to identify potential issues before they escalate into significant problems, thereby minimising downtime and enhancing operational efficiency.

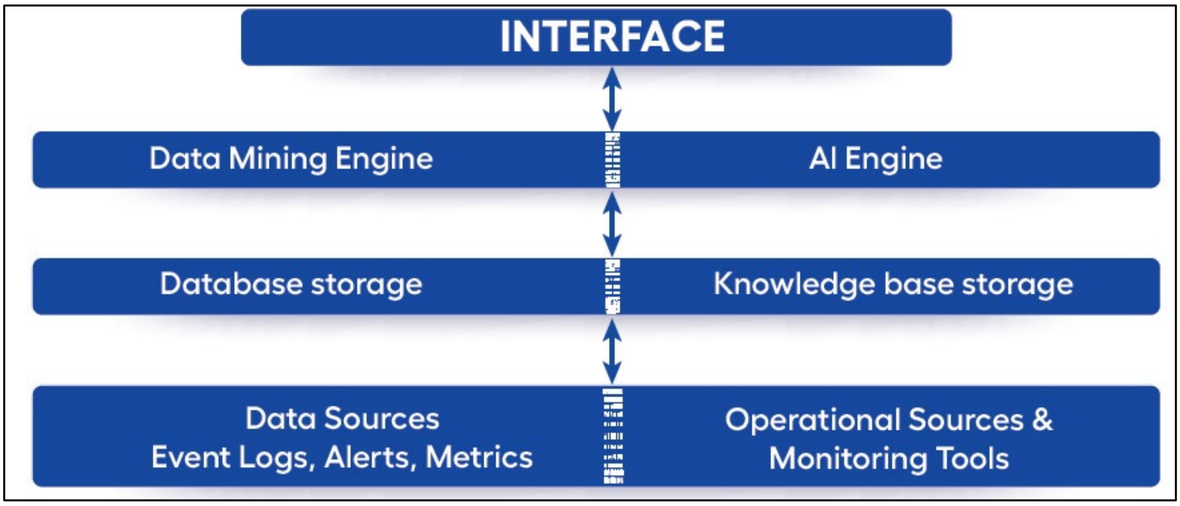


Figure 5.5 AIDSS Data infrastructure (adapted from Abu-Naser *et al.*, 2011)

Shown in Figure 5.5 above is the data infrastructure of AIDSS, which necessitates robust planning and design. The infrastructure’s four layers collaborate to gather, store, handle and evaluate data. This information can be utilised to enhance decision making recognise patterns and address challenges as elaborated in the description of the four layers below:

The First Layer

The user interface of the AIDSS presents appealing and designed graphical representations. These visuals effectively communicate the insights and outcomes generated from executing tasks within the system. Through utilising these interfaces users can access a depiction of the data driven insights and recommendations provided by AIDSS. This approach enhances accessibility and understanding of information empowering users to make decisions with confidence, supported by the intelligent capabilities of the system.

The Second Layer

The AI engine takes the results of its completed tasks. Converts them into information, which is then stored in a specialised knowledge database. Afterwards these findings are displayed on the user interface in a way that's intelligent and personalised to meet the users' preferences creating a user-friendly presentation. AIDSS data repositories receive information from records or existing datasets. The data in these repositories must be prepared in advance to ensure that it is properly formatted for DSS tasks.

The Third Layer

Storage repositories contain information and regulations related to tasks, data and the field of data mining. Initially the AIDSS developer fills these repositories with knowledge and regulations. As AIDSS tasks are performed over time the database and knowledge repository are enriched with knowledge and rules acquired from their execution.

The Fourth Layer

The AIDSS employs monitoring tools, alerts, event logs and metrics to gather information about the ICT environment. This information can be utilised to detect issues, patterns and potential opportunities. Through the monitoring tools data is collected concerning the performance of the ICT infrastructure. By analysing this data problems can be identified such as a server or a congested network. Alerts are employed to notify ICT personnel about problems. Event logs maintain a record of all activities occurring within the ICT environment including user logins, file access events and application errors. These logs enable tracking of user and application behaviour as identifying security breaches. Metrics play a role in assessing the performance of the ICT environment by measuring factors such as transaction frequency per response time for web requests. This data aids in monitoring long term performance trends and identifying areas where enhancements can be implemented.

AIDSS Artefact Design

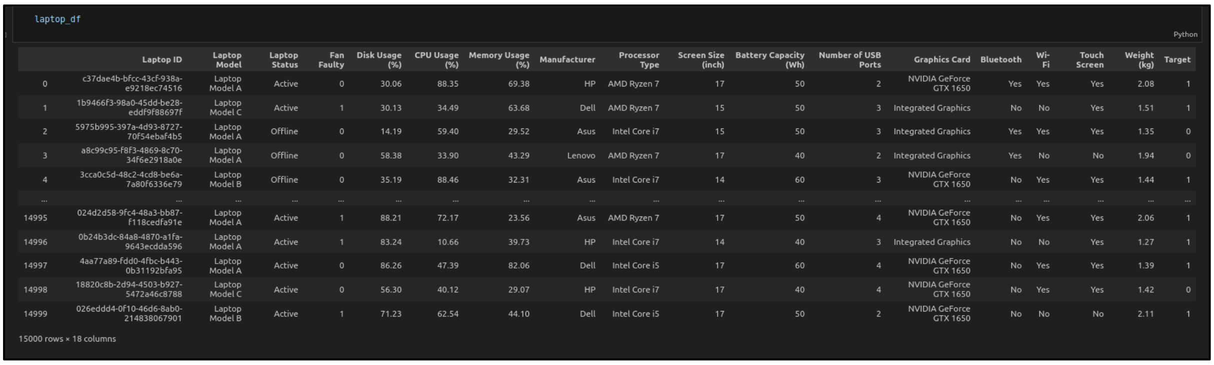
The development of the Artificial intelligence-enabled decision support system to support operational decision-making within the ICT department at the university involved a comprehensive methodology encompassing data collection, preprocessing, model training and deployment. The fault detection models were trained and evaluated using a range of machine learning algorithms. The ChatBot's (BPABot) implementation hinges on the integration of the GPT-3.5-turbo model, which enables sophisticated natural language processing capabilities. The AIDSS prototype was designed to proactively engage in Preventative Maintenance and Predictive Analytics for identifying faults in laptops and servers. This functionality was implemented using Python to create a fault detection element.

5.3 Data collection and preprocessing

As detailed in Activity Four, the AIDSS prototype goes through a training process where it learns from data to enhance its decision-making capabilities. Afterward an evaluation of its performance compared its predictions with data to ensure efficient decision support.The foundation of the AIDSS lies in data. Dummy datasets simulating real-world scenarios were employed for both laptop and server fault detection. Each dataset contains relevant attributes such as disk usage, CPU usage and memory usage. A preprocessing pipeline was established to transform the raw data into a suitable format for model training. This involved one-hot encoding categorical variables and standardising numerical features. One of the most important steps in data preprocessing is to encode categorical variables. Categorical variables are variables that can take on a limited number of values, such as laptop model and manufacturer. These variables need to be encoded so that they can be used by machine learning algorithms. Data preprocessing has advantages when it comes to preparing data for machine learning tasks. One of its benefits is that it effectively removes noise from the data, making the datasets cleaner and more reliable. It also helps in identifying and handling outliers which are data points that significantly deviate from the norm and could potentially disrupt the learning process. Additionally, data preprocessing deals with missing values to ensure a dataset for thorough analysis. Furthermore, it involves transforming data into formats that best suit machine learning algorithms thus optimising their performance and predictive accuracy.

i) Laptop dataset

Dummy data is often used when real-world data is not available or when it is too expensive to collect. As shown in Figure 5.6, dummy data was created to simulate real-world data. This data is used to train the AIDSS to make predictions that are accurate in the simulated world.



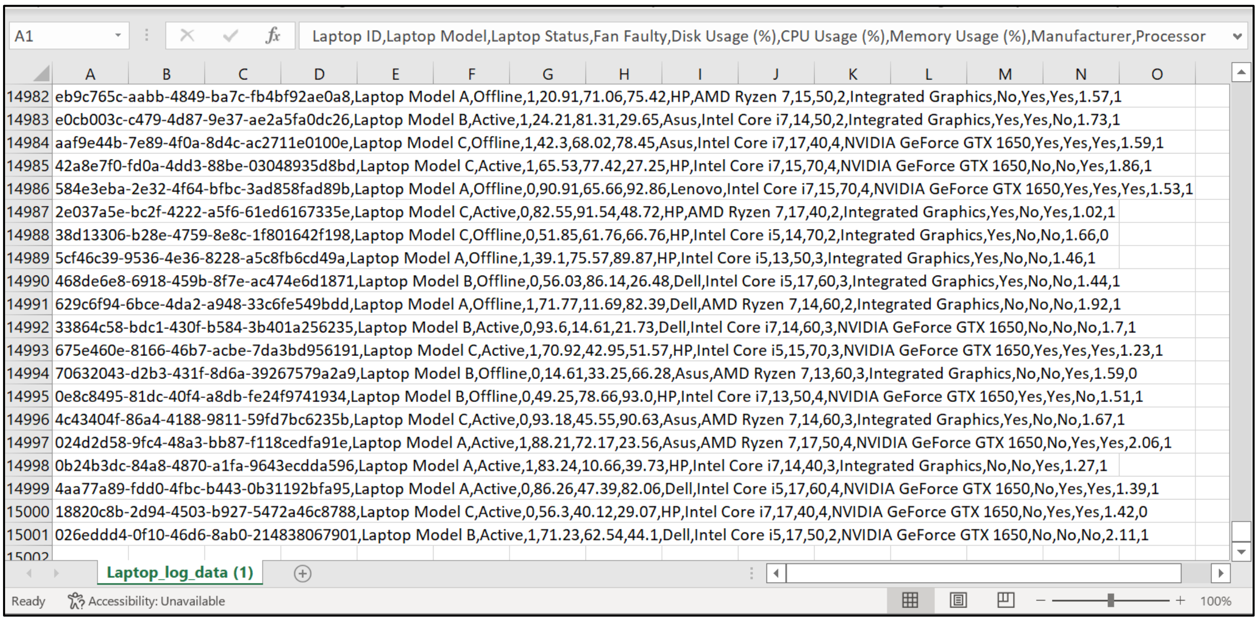
```
laptop_df
```

	Laptop ID	Laptop Model	Laptop Status	Fan Faulty	Disk Usage (%)	CPU Usage (%)	Memory Usage (%)	Manufacturer	Processor Type	Screen Size (inch)	Battery Capacity (Wh)	Number of USB Ports	Graphics Card	Bluetooth	Wi-Fi	Touch Screen	Weight (kg)	Target
0	c37dae4b-bfcc-43cf-938a-e9218ec74516	Laptop Model A	Active	0	30.06	88.35	69.38	HP	AMD Ryzen 7	17	50	2	NVIDIA GeForce GTX 1650	Yes	Yes	Yes	2.08	1
1	1b9466f3-98a0-45dd-be28-eddf9f88697f	Laptop Model C	Active	1	30.13	34.49	63.68	Dell	AMD Ryzen 7	15	50	3	Integrated Graphics	No	No	Yes	1.51	1
2	5975b995-397a-4d93-8727-70f54ebaf4b5	Laptop Model A	Offline	0	14.19	59.40	29.52	Asus	Intel Core i7	15	50	3	Integrated Graphics	Yes	Yes	Yes	1.35	0
3	a8c99c95-f8f3-4869-8c70-34f6e2918a0e	Laptop Model A	Offline	0	58.38	33.90	43.29	Lenovo	AMD Ryzen 7	17	40	2	Integrated Graphics	Yes	No	No	1.94	0
4	3cca0c5d-48c2-4cd8-be6a-7a80f6336e79	Laptop Model B	Offline	0	35.19	88.46	32.31	Asus	Intel Core i7	14	60	3	NVIDIA GeForce GTX 1650	No	Yes	Yes	1.44	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
14995	024d2d58-9fc4-48a3-bb87-f118cedfa91e	Laptop Model A	Active	1	88.21	72.17	23.56	Asus	AMD Ryzen 7	17	50	4	NVIDIA GeForce GTX 1650	No	Yes	Yes	2.06	1
14996	0b24b3dc-84a8-4870-a1fa-9643ecdda596	Laptop Model A	Active	1	83.24	10.66	39.73	HP	Intel Core i7	14	40	3	Integrated Graphics	No	No	Yes	1.27	1
14997	4aa77a89-fdd0-4fbc-b443-0b31192bfa95	Laptop Model A	Active	0	86.26	47.39	82.06	Dell	Intel Core i5	17	60	4	NVIDIA GeForce GTX 1650	No	Yes	Yes	1.39	1
14998	18820c8b-2d94-4503-b927-5472a46c8788	Laptop Model C	Active	0	56.30	40.12	29.07	HP	Intel Core i7	17	40	4	NVIDIA GeForce GTX 1650	No	Yes	Yes	1.42	0
14999	026eddd4-0f10-46d6-8ab0-214838067901	Laptop Model B	Active	1	71.23	62.54	44.10	Dell	Intel Core i5	17	50	2	NVIDIA GeForce GTX 1650	No	No	No	2.11	1

15000 rows × 18 columns

Figure 5.6 Laptop dataset

The diversity in the dataset ensured that the model was exposed to various laptop configurations, allowing it to recognise patterns and anomalies associated with different faults. The "Target" variable served as a label indicating the presence or absence of faults, enabling the model to learn from examples in a supervised learning approach.



A1 — Laptop ID,Laptop Model,Laptop Status,Fan Faulty,Disk Usage (%),CPU Usage (%),Memory Usage (%),Manufacturer,Processor

	A
14982	eb9c765c-aabb-4849-ba7c-fb4bf92ae0a8,Laptop Model A,Offline,1,20.91,71.06,75.42,HP,AMD Ryzen 7,15,50,2,Integrated Graphics,No,Yes,Yes,1.57,1
14983	e0cb003c-c479-4d87-9e37-ae2a5fa0dc26,Laptop Model B,Active,1,24.21,81.31,29.65,Asus,Intel Core i7,14,50,2,Integrated Graphics,Yes,Yes,No,1.73,1
14984	aaf9e44b-7e89-4f0a-8d4c-ac2711e0100e,Laptop Model C,Offline,1,42.3,68.02,78.45,Asus,Intel Core i7,17,40,4,NVIDIA GeForce GTX 1650,Yes,Yes,Yes,1.59,1
14985	42a8e7f0-fd0a-4dd3-88be-03048935d8bd,Laptop Model C,Active,1,65.53,77.42,27.25,HP,Intel Core i7,15,70,4,NVIDIA GeForce GTX 1650,No,No,Yes,1.86,1
14986	584e3eba-2e32-4f64-bfbc-3ad858fad89b,Laptop Model A,Offline,0,90.91,65.66,92.86,Lenovo,Intel Core i7,15,70,4,NVIDIA GeForce GTX 1650,Yes,Yes,Yes,1.53,1
14987	2e037a5e-bc2f-4222-a5f6-61ed6167335e,Laptop Model C,Active,0,82.55,91.54,48.72,HP,AMD Ryzen 7,17,40,2,Integrated Graphics,Yes,No,Yes,1.02,1
14988	38d13306-b28e-4759-8e8c-1f801642f198,Laptop Model C,Offline,0,51.85,61.76,66.76,HP,Intel Core i5,14,70,2,Integrated Graphics,Yes,No,No,1.66,0
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14990	468de6e8-6918-459b-8f7e-ac474e6d1871,Laptop Model B,Offline,0,56.03,86.14,26.48,Dell,Intel Core i5,17,60,3,Integrated Graphics,Yes,No,No,1.44,1
14991	629c6f94-6bce-4da2-a948-33c6fe549bdd,Laptop Model A,Offline,1,71.77,11.69,82.39,Dell,AMD Ryzen 7,14,60,2,Integrated Graphics,No,No,No,1.92,1
14992	33864c58-bdc1-430f-b584-3b401a256235,Laptop Model B,Active,0,93.6,14.61,21.73,Dell,Intel Core i7,14,60,3,NVIDIA GeForce GTX 1650,No,No,No,1.7,1
14993	675e460e-8166-46b7-acbe-7da3bd956191,Laptop Model C,Active,1,70.92,42.95,51.57,HP,Intel Core i5,15,70,3,NVIDIA GeForce GTX 1650,Yes,Yes,Yes,1.23,1
14994	70632043-d2b3-431f-8d6a-39267579a2a9,Laptop Model B,Offline,0,14.61,33.25,66.28,Asus,AMD Ryzen 7,13,60,3,Integrated Graphics,No,No,Yes,1.59,0
14995	0e8c8495-81dc-40f4-a8db-fe24f9741934,Laptop Model B,Offline,0,49.25,78.66,93.0,HP,Intel Core i7,13,50,4,NVIDIA GeForce GTX 1650,Yes,Yes,No,1.51,1
14996	4c43404f-86a4-4188-9811-59fd7bc6235b,Laptop Model C,Active,0,93.18,45.55,90.63,Asus,AMD Ryzen 7,14,60,3,Integrated Graphics,Yes,No,No,1.67,1
14997	024d2d58-9fc4-48a3-bb87-f118cedfa91e,Laptop Model A,Active,1,88.21,72.17,23.56,Asus,AMD Ryzen 7,17,50,4,NVIDIA GeForce GTX 1650,No,Yes,Yes,2.06,1
14998	0b24b3dc-84a8-4870-a1fa-9643ecdda596,Laptop Model A,Active,1,83.24,10.66,39.73,HP,Intel Core i7,14,40,3,Integrated Graphics,No,No,Yes,1.27,1
14999	4aa77a89-fdd0-4fbc-b443-0b31192bfa95,Laptop Model A,Active,0,86.26,47.39,82.06,Dell,Intel Core i5,17,60,4,NVIDIA GeForce GTX 1650,No,Yes,Yes,1.39,1
15000	18820c8b-2d94-4503-b927-5472a46c8788,Laptop Model C,Active,0,56.3,40.12,29.07,HP,Intel Core i7,17,40,4,NVIDIA GeForce GTX 1650,No,Yes,Yes,1.42,0
15001	026eddd4-0f10-46d6-8ab0-214838067901,Laptop Model B,Active,1,71.23,62.54,44.1,Dell,Intel Core i5,17,50,2,NVIDIA GeForce GTX 1650,No,No,No,2.11,1

Figure 5.7 Laptop raw data

Laptop raw data consisting of 15,000 records to train the laptop fault detection model (Figure 5.7). The laptop fault detection model, trained on a dataset comprising 15,000 records, demonstrated promising efficacy in identifying and diagnosing laptop faults. The dataset encompasses crucial parameters such as Laptop ID, Laptop Model, Laptop Status, Fan Faulty, Disk Usage (%), CPU Usage (%), Memory Usage (%), Manufacturer, Processor Type, Screen Size (inch), Battery Capacity (Wh), Number of USB Ports, Graphics Card, Bluetooth, Wi-Fi, Touch Screen, Weight (kg), and a Target variable. By leveraging this comprehensive dataset, the model gains a nuanced understanding of diverse laptop configurations and associated faults, enabling accurate and reliable fault detection. This approach holds potential for enhancing laptop diagnostics, streamlining maintenance, and optimising overall system performance. The accuracy of the model depends on the quality of the data used to train it. Extra care was taken to clean the data, so that it is free of errors and inconsistencies. If the data is not representative of the real world, the model may not be able to identify faults accurately.

```
server_df
```

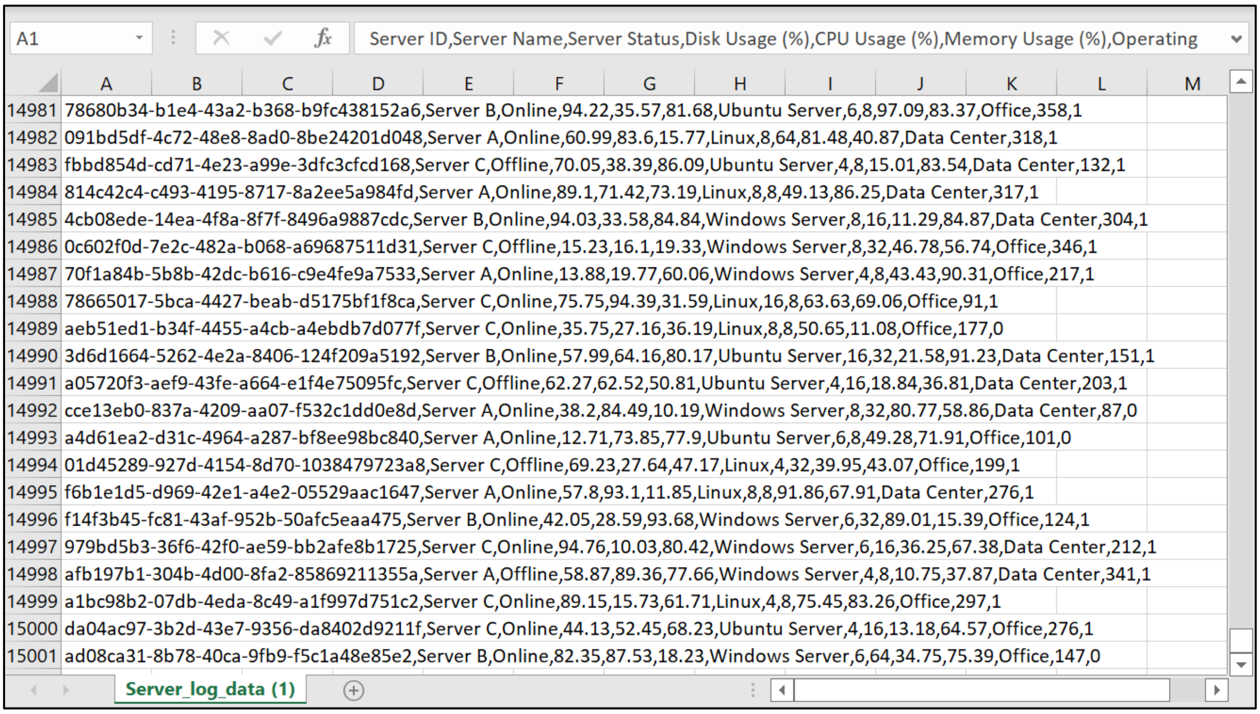
Python

	Server ID	Server Name	Server Status	Disk Usage (%)	CPU Usage (%)	Memory Usage (%)	Operating System	Number of CPU Cores	RAM Capacity (GB)	Network Traffic (Mbps)	Disk I/O (IOPS)	Server Location	Server Uptime (days)	Target
0	0560324d-9473-4601-9c36-663d91b1cc52	Server C	Offline	93.05	11.51	56.95	Linux	16	16	40.37	26.64	Data Center	230	1
1	b8baa62c-68d9-4257-9fd2-679ead3de617	Server C	Offline	70.71	52.34	80.44	Windows Server	6	64	35.32	69.85	Office	146	0
2	f240e773-15a5-4688-af7c-5b68aff2e679	Server A	Offline	45.90	36.88	90.65	Ubuntu Server	16	8	22.32	16.49	Office	136	1
3	a6d5bf90-c43f-40c8-929e-a27f34f3d20f	Server A	Online	33.50	13.56	64.80	Linux	8	8	98.19	75.33	Office	140	1
4	c3fea11b-838c-4316-9203-e088b6768555	Server C	Online	82.50	24.92	80.64	Windows Server	8	8	38.75	52.07	Data Center	338	1
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
14995	979bd5b3-36f6-42f0-ae59-bb2afe8b1725	Server C	Online	94.76	10.03	80.42	Windows Server	6	16	36.25	67.38	Data Center	212	1
14996	afb197b1-304b-4d00-8fa2-85869211355a	Server A	Offline	58.87	89.36	77.66	Windows Server	4	8	10.75	37.87	Data Center	341	1
14997	a1bc98b2-07db-4eda-8c49-a1f997d751c2	Server C	Online	89.15	15.73	61.71	Linux	4	8	75.45	83.26	Office	297	1
14998	da04ac97-3b2d-43e7-9356-da8402d9211f	Server C	Online	44.13	52.45	68.23	Ubuntu Server	4	16	13.18	64.57	Office	276	1
14999	ad08ca31-8b78-40ca-9fb9-f5c1a48e85e2	Server B	Online	82.35	87.53	18.23	Windows Server	6	64	34.75	75.39	Office	147	0

15000 rows × 14 columns

Figure 5.8 Server dataset

In the case of the AIDSS as per Figure 5.8, dummy datasets simulating real-world scenarios was employed for both laptop and server fault detection. This was done because real-world data for these two tasks can be difficult to collect and it can be expensive to store and process.



A1: Server ID,Server Name,Server Status,Disk Usage (%),CPU Usage (%),Memory Usage (%),Operating

	A
14981	78680b34-b1e4-43a2-b368-b9fc438152a6,Server B,Online,94.22,35.57,81.68,Ubuntu Server,6,8,97.09,83.37,Office,358,1
14982	091bd5df-4c72-48e8-8ad0-8be24201d048,Server A,Online,60.99,83.6,15.77,Linux,8,64,81.48,40.87,Data Center,318,1
14983	fbbd854d-cd71-4e23-a99e-3dfc3cfcd168,Server C,Offline,70.05,38.39,86.09,Ubuntu Server,4,8,15.01,83.54,Data Center,132,1
14984	814c42c4-c493-4195-8717-8a2ee5a984fd,Server A,Online,89.1,71.42,73.19,Linux,8,8,49.13,86.25,Data Center,317,1
14985	4cb08ede-14ea-4f8a-8f7f-8496a9887cdc,Server B,Online,94.03,33.58,84.84,Windows Server,8,16,11.29,84.87,Data Center,304,1
14986	0c602f0d-7e2c-482a-b068-a69687511d31,Server C,Offline,15.23,16.1,19.33,Windows Server,8,32,46.78,56.74,Office,346,1
14987	70f1a84b-5b8b-42dc-b616-c9e4fe9a7533,Server A,Online,13.88,19.77,60.06,Windows Server,4,8,43.43,90.31,Office,217,1
14988	78665017-5bca-4427-beab-d5175bf1f8ca,Server C,Online,75.75,94.39,31.59,Linux,16,8,63.63,69.06,Office,91,1
14989	aeb51ed1-b34f-4455-a4cb-a4ebdb7d077f,Server C,Online,35.75,27.16,36.19,Linux,8,8,50.65,11.08,Office,177,0
14990	3d6d1664-5262-4e2a-8406-124f209a5192,Server B,Online,57.99,64.16,80.17,Ubuntu Server,16,32,21.58,91.23,Data Center,151,1
14991	a05720f3-aef9-43fe-a664-e1f4e75095fc,Server C,Offline,62.27,62.52,50.81,Ubuntu Server,4,16,18.84,36.81,Data Center,203,1
14992	cce13eb0-837a-4209-aa07-f532c1dd0e8d,Server A,Online,38.2,84.49,10.19,Windows Server,8,32,80.77,58.86,Data Center,87,0
14993	a4d61ea2-d31c-4964-a287-bf8ee98bc840,Server A,Online,12.71,73.85,77.9,Ubuntu Server,6,8,49.28,71.91,Office,101,0
14994	01d45289-927d-4154-8d70-1038479723a8,Server C,Offline,69.23,27.64,47.17,Linux,4,32,39.95,43.07,Office,199,1
14995	f6b1e1d5-d969-42e1-a4e2-05529aac1647,Server A,Online,57.8,93.1,11.85,Linux,8,8,91.86,67.91,Data Center,276,1
14996	f14f3b45-fc81-43af-952b-50afc5eaa475,Server B,Online,42.05,28.59,93.68,Windows Server,6,32,89.01,15.39,Office,124,1
14997	979bd5b3-36f6-42f0-ae59-bb2afe8b1725,Server C,Online,94.76,10.03,80.42,Windows Server,6,16,36.25,67.38,Data Center,212,1
14998	afb197b1-304b-4d00-8fa2-85869211355a,Server A,Offline,58.87,89.36,77.66,Windows Server,4,8,10.75,37.87,Data Center,341,1
14999	a1bc98b2-07db-4eda-8c49-a1f997d751c2,Server C,Online,89.15,15.73,61.71,Linux,4,8,75.45,83.26,Office,297,1
15000	da04ac97-3b2d-43e7-9356-da8402d9211f,Server C,Online,44.13,52.45,68.23,Ubuntu Server,4,16,13.18,64.57,Office,276,1
15001	ad08ca31-8b78-40ca-9fb9-f5c1a48e85e2,Server B,Online,82.35,87.53,18.23,Windows Server,6,64,34.75,75.39,Office,147,0

Server_log_data (1)

Figure 5.9 Server raw data

A dataset comprising 15,000 individual pieces of raw server-related data (Figure 5.9). This data is employed in the training process of the AIDSS model to identify instances of server malfunctions or faults. Machine learning algorithms were applied to the dataset, and the model was trained to generalize from the data, capturing underlying relationships between features and the occurrence of faults. The dataset was used for fine-tuning and validation, ensuring the model's accuracy and generalisation to unseen data. Once trained, the model could analyse new input data, such as attributes of a laptop or server, and predict the likelihood of faults based on the learned patterns from the dataset. The training involves feeding this dataset into the model, allowing it to learn and recognise patterns associated with server failures. This enables the model to accurately predict and flag potential issues in real-time server operations.

5.3.1 Machine Learning Models for Fault Detection

The heart of the fault detection aspect lies in machine learning models. Four diverse algorithms were selected for their ability to handle classification tasks effectively: Logistic Regression, Random Forest, Support Vector Classifier (SVC), and Decision Tree. As detailed below, the models underwent rigorous training and evaluation processes using classification reports and ROC-AUC curves to gauge their performance.

5.3.2 BPAChatBot Implementation

The BPABot was conceived to enhance requests for business process automation and streamline communication. The chatbot was built using Botpress, a no-code chatbot platform. The chatbot can be embedded on any website or operated as a standalone web application. The information submitted by users through the chatbot is stored in a database table. The integration of OpenAI's GPT-3.5-turbo model enables the chatbot to generate contextually relevant responses. The BPAChatBot interacts with employees, collects user and business process information and BPA requests seamlessly. In the AIDSS being proposed the term "conversation flow" refers to the sequence in which users engage with the BPAChatBot.

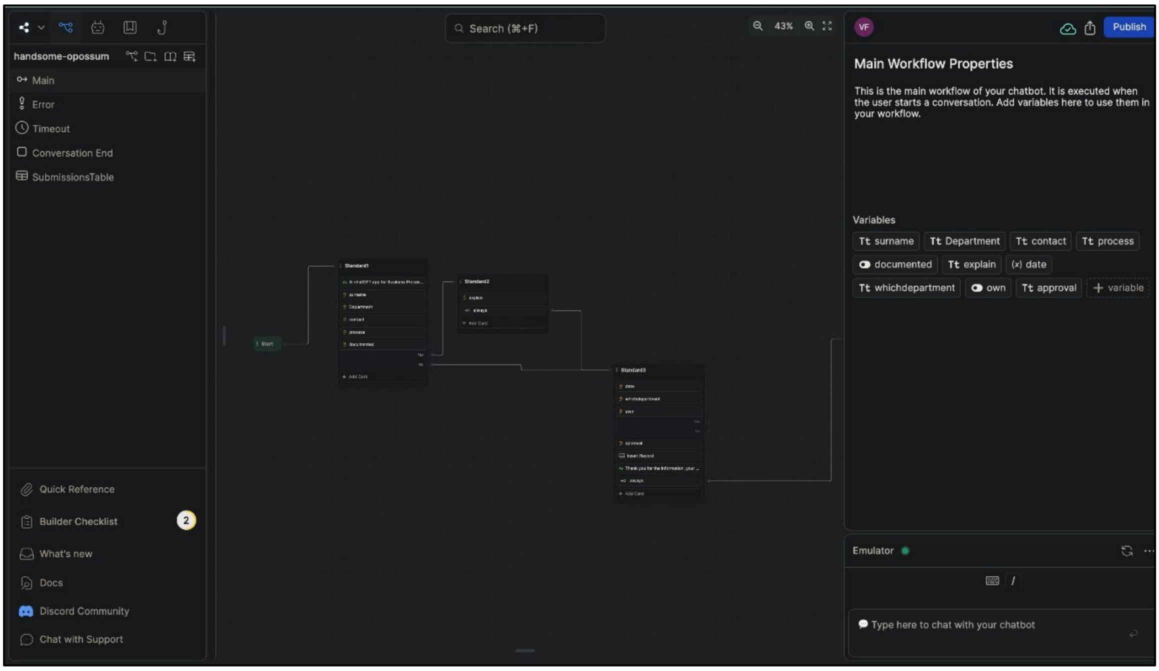


Figure 5.10 BPAChatBot Conversation flow

BPAChatBot conversation flow outlines the progression of dialogues beginning with user's initial inputs and continuing through the systems generated responses and subsequent enquiries. As shown in Figure 5.10 above, this flow follows predefined rules and logical patterns to ensure an organised exchange of information.

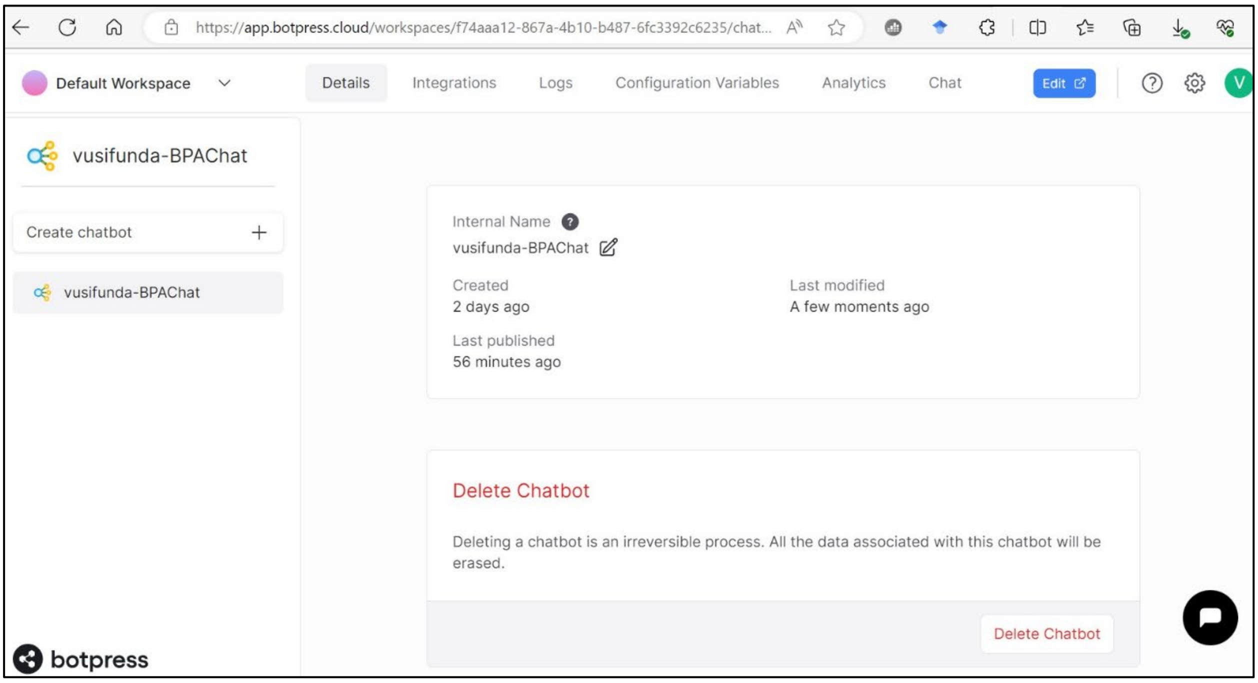


Figure 5.11 BPAChatBot configuration

As reflected in Figure 5.11 above, the BPAChatBot is impressively versatile allowing it to be smoothly incorporated into websites or used as a web application. When users engage with the chatbot they can confidently enter their information knowing that it will be securely captured and organised in a dedicated database table. This organised storage system ensures that user provided data, through the chatbot can be easily accessed and retrieved for reference or analysis enhancing the user experience by making it more streamlined and efficient.

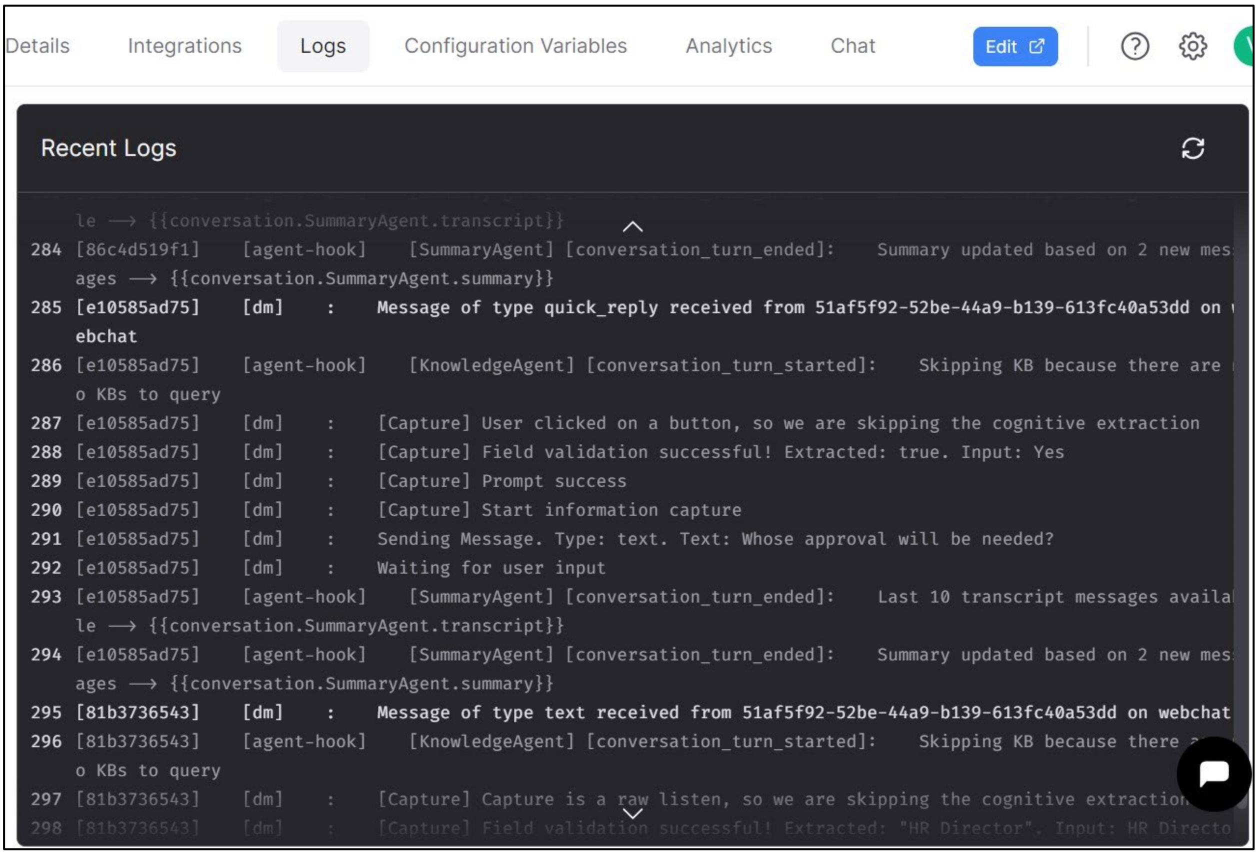


Figure 5.12 BPAChatBot logs

Figure 5.12 shows above the BPAChatBot logs. In addition to being highly adaptable the BPAChatBot also includes a logging feature that meticulously keeps track of every interaction and conversation with users. This logging system captures all inputs, queries and responses throughout the conversation. The logs are carefully stored in a repository allowing for review of past interactions for analysis and quality assurance purposes. This logging capability not only serve as a reference for users who want to revisit previous discussions but also offers administrators and developers valuable insights into user requests. Overall, this contributes to enhancing the performance of the chatbot and ensuring user satisfaction.

5.3.3 Laptop Preprocessing Pipeline

The laptop fault detection model's success hinges on data preprocessing. Categorical variables, including laptop model and manufacturer, underwent one-hot encoding. One-hot encoding creates a new binary variable for each possible value of the categorical variable. For example in figure 5.13, if the laptop model variable can take on the values "Dell", "HP", and "Lenovo", then one-hot encoding would create three new binary variables: "is_Dell", "is_HP", and "is_Lenovo". Numerical features such as disk usage and battery capacity were standardised to ensure consistent scales for model input. By preprocessing the data, the AIDSS can improve the accuracy and performance of the laptop fault detection model. The model will be able to learn from the data more effectively and make more accurate predictions.

```python
# Preprocessing pipeline for Scenario 1 (Laptops)
def preprocess_laptop_data(df):
    # Select features and target variable
    X = df.drop(columns=['Laptop ID', 'Target'])
    y = df['Target']

    # Encode categorical variables (Laptop Model, Laptop Status, Manufacturer, Processor Type, Graphics Card, Bluetooth, Wi-Fi, Touch Screen)
    categorical_features = ['Laptop Model', 'Laptop Status', 'Manufacturer', 'Processor Type', 'Graphics Card', 'Bluetooth', 'Wi-Fi', 'Touch Screen']
    categorical_transformer = OneHotEncoder(drop='first')

    # Scale numerical features (Disk Usage (%), CPU Usage (%), Memory Usage (%), Screen Size (inch), Battery Capacity (Wh), Number of USB Ports, Weight (kg))
    numerical_features = ['Disk Usage (%)', 'CPU Usage (%)', 'Memory Usage (%)', 'Screen Size (inch)', 'Battery Capacity (Wh)', 'Number of USB Ports', 'Weight (kg)']
    numerical_transformer = StandardScaler()

    # Combine the transformations
    preprocessor = ColumnTransformer(
        transformers=[
            ('cat', categorical_transformer, categorical_features),
            ('num', numerical_transformer, numerical_features)
        ])

    # saving the preprocessing pipeline

    joblib.dump(preprocessor, 'laptop_preprocessor_pipeline.joblib')

    preprocessor_ = joblib.load('laptop_preprocessor_pipeline.joblib')

    # Apply preprocessing to the data
    X_preprocessed = preprocessor.fit_transform(X)

    # Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X_preprocessed, y, test_size=0.2, random_state=42)

    return X_train, X_test, y_train, y_test
```

Figure 5.13 Preprocessing pipeline for the laptop dataset

5.3.4 Server Preprocessing Pipeline

Like the laptop pipeline, server data underwent preprocessing to ensure consistent input for the fault detection models (Figure 5.14). Categorical variables like server status and operating system were one-hot encoded, and numerical attributes were standardised. Numerical features such as disk usage and server status need to be pre-processed. These features can have different scales which can make it difficult for machine learning algorithms to learn from the data. Standardisation is a process that transforms the numerical features so that they have a mean of 0 and a standard deviation of 1. This ensures that all the features are on the same scale, which makes it easier for the machine learning algorithms to learn from the data.

```python
# Preprocessing pipeline for Scenario 2 (Servers)
def preprocess_server_data(df):
    # Select features and target variable
    X = df.drop(columns=['Server ID', 'Server Name', 'Target'])
    y = df['Target']

    # Encode categorical variables (Server Status, Operating System, Server Location)
    categorical_features = ['Server Status', 'Operating System', 'Server Location']
    categorical_transformer = OneHotEncoder(drop='first')

    # Scale numerical features (Disk Usage (%), CPU Usage (%), Memory Usage (%), Number of CPU Cores, RAM Capacity (GB), Network Traffic (Mbps), Disk I/O (IOPS), Server Uptime (days))
    numerical_features = ['Disk Usage (%)', 'CPU Usage (%)', 'Memory Usage (%)', 'Number of CPU Cores', 'RAM Capacity (GB)', 'Network Traffic (Mbps)', 'Disk I/O (IOPS)', 'Server Uptime (days)']
    numerical_transformer = StandardScaler()

    # Combine the transformations
    preprocessor = ColumnTransformer(
        transformers=[
            ('cat', categorical_transformer, categorical_features),
            ('num', numerical_transformer, numerical_features)
        ])
    # saving the preprocessing pipeline

    joblib.dump(preprocessor, 'server_preprocessor_pipeline.joblib')

    preprocessor_ = joblib.load('server_preprocessor_pipeline.joblib')
    # Apply preprocessing to the data
    X_preprocessed = preprocessor_.fit_transform(X)

    # Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X_preprocessed, y, test_size=0.2, random_state=42)

    return X_train, X_test, y_train, y_test
```
Python

Figure 5.14 Preprocessing pipeline for the server dataset

5.4 Activity 4: Test the Artefact

The AIDSS is a powerful tool that can help the ICT department make better decisions. By harnessing the power of AI, the system can provide insights and recommendations that would not be possible with traditional decision-making methods. In this model testing phase, the trained model is exposed to unseen data to simulate real life situations. This evaluation measures how well the model performs by assessing its ability to provide recommendations or predictions. Metrics such, as accuracy, precision, recall are calculated to determine its effectiveness. The iterative process of training and testing ensures that the AIDSS model is reliable, adaptable and capable of providing decision support in scenarios. Consequently, the system can be used to identify trends in the department's data. This information can be used to make predictions about future demand for services or to identify areas where the department can improve its efficiency.

i) BPAChatBot Web interface

In the proposed AIDSS the conversation flow refers to the order in which users interact with AI powered systems such as chatbots. It outlines how conversations progress, starting from the user's input and continuing with the system's responses and subsequent queries. This flow is guided by predefined rules and logic to ensure that information is exchanged coherently. It all begins with the users' input (Figure 5.15) which is then analysed using natural language processing to understand their intent. Based on this understanding the system generates responses and prompts for interaction. The flow branches out based on user responses using decision trees to determine what happens next. Multi turn interactions allow for an addressing of user queries ultimately leading to resolutions or desired outcomes. Fallback strategies are in place to handle situations where the system faces challenges. Throughout this process ontext is maintained so that the system can refer to interactions. Designing a conversation flow guarantees responses thereby improving user experience and facilitating successful interactions with the AIDSS.

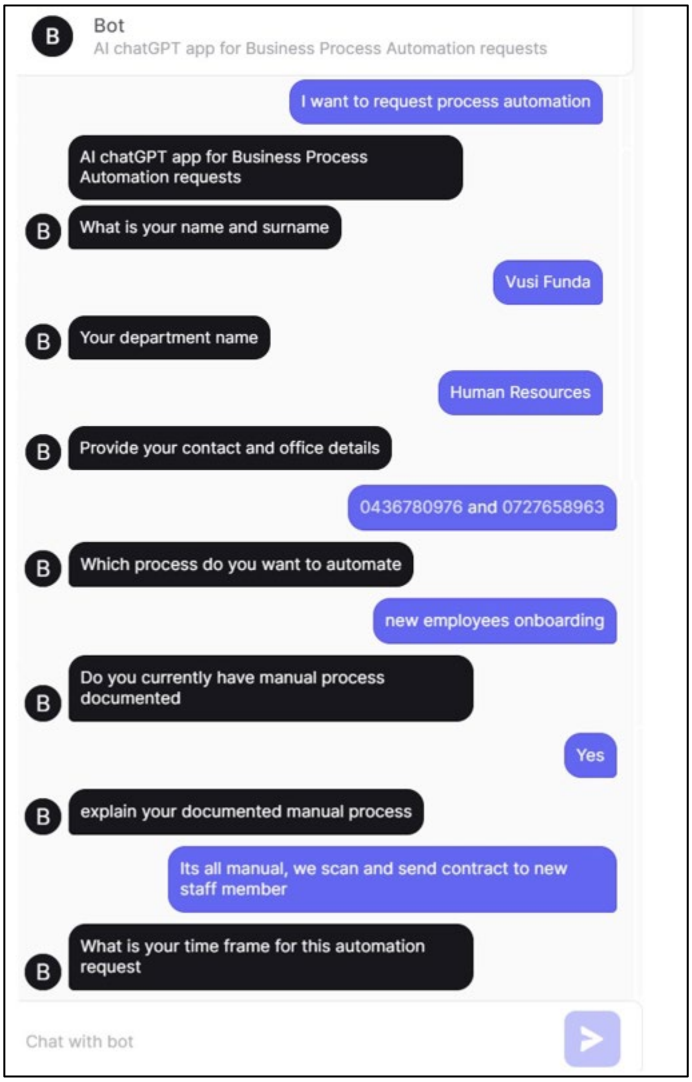


Figure 5.15 BPAChatBot

As shown in Figure 5.15 is an example of BPAChatBot Conversation Flow. The BPAChatBot allows users to interact and gather business process requirements. It's a time saving tool for the BPM who would otherwise have to collect this information manually. With the BPAChatBot users can be asked questions about their business processes. The chatbot also helps in understanding the users' needs such as their goals and the problems they aim to solve through the process. Once all necessary information is gathered the BPAChatBot can send it via email as a text file that includes user details and request information to the BPM and store it in the

AIDSS. This streamlined process ensures that the BPM has access to all information needed for designing and automating the required business processes. The chatbot can help to save time, improve accuracy and improve efficiency and decision-making.

ii) AIDSS Artefact

The aim of the study was to develop an Artificial Intelligence-enabled Decision Support System. In this section we present the AIDSS artefact which operates seamlessly on the Streamlit web interface. Streamlit is a Python library that allows developers to create interactive web applications directly from Python scripts. Streamlit handles the conversion of Python code into a web application, eliminating the need for separate HTML, CSS, or JavaScript coding. The AIDSS was developed using Python library and is equipped with robust functionalities, including business automation, preventative asset maintenance, and predictive analytics. This marks a commendable stride in addressing identified issues and elevating operational efficiency. The AIDSS enhances accessibility but also signifies a user-friendly and interactive platform for leveraging AI capabilities. This AIDSS represents a significant advancement, showcasing the commitment to innovation and strategic problem-solving in the pursuit of operational excellence. The interface features three prominent icons on the left, each representing distinct functionalities: Preventative Maintenance, Prediction Analytics, and BPAChatbot. The Preventative Maintenance and Prediction Analytics components are specifically designed to address laptop fault detection and server fault detection, respectively. An illustration of the AIDSS interface is shown in Figure 5.16.

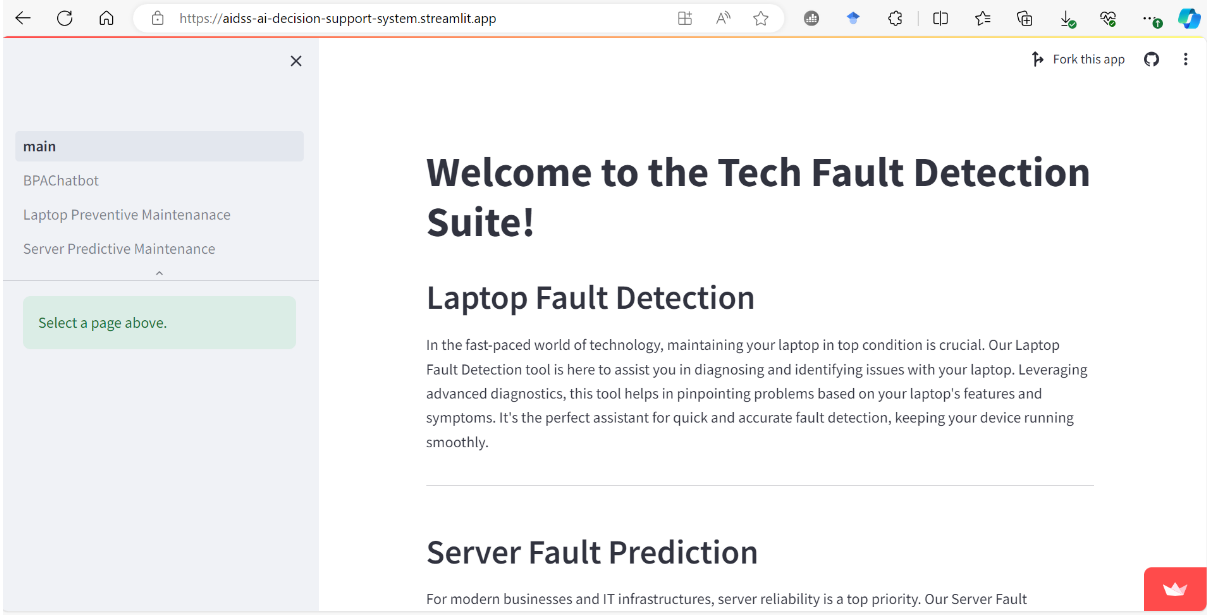


Figure 5.16 AIDSS interface

The AIDSS empowers users to run a query, triggering fault predictions. The interface showcases the AIDSS's practicality, providing real-time results, it is an intuitive platform for laptop and server fault detection. By focusing on these anomalies within the logs, the ICT Team has the potential to proactively avert future system failures. The integration of the BPAChatBot further elevates user experience, providing timely and contextually relevant responses, marking a convergence of technology and IT operations within the ICT department.

The interface is designed to be easy to use even for users with no programming experience. To use the interface, users first need to select the type of device they want to monitor. Once the device is selected, the interface will then run the query and generate a report of the state of that particular asset. The report will be displayed in real time so that the IT team can see the results as they are happening. The results are emailed to the dedicated person or helpdesk in the ICT department to decide. This feature can also be embedded on the call logging system such that the AIDSS logs a call directly on the system. The AIDSS can be used to improve decision-making in several ways. First, it can help the IT team to identify potential problems before they happen. This can help to prevent costly system failures. Second, the AIDSS can help the IT team to prioritise their resources. By identifying the devices that are most likely to fail, the ICT department can focus their attention on those devices and prevent problems from spreading.

iii) Fault Detection Models for Laptops (Preventative Maintenance)

This icon leads to a module focused on proactively maintaining laptops. It incorporates advanced algorithms and data analysis to identify potential issues before they escalate into faults. Users can access features related to optimising laptop performance, addressing common problems, and implementing preventive measures based on current state and historical fault data. Encompassing tasks such as scanning computer devices like laptops to identify hardware faults. This helps predict when maintenance is needed more accurately and on time. This smart way of preventative maintenance can help the ICT team make schedules that work better, avoiding unnecessary work and costs. This AI-powered method also helps the ICT department make better decisions based on data. This capability extends to enhancing asset lifespan and resource allocation efficiency. The section for fault detection in laptops is shown in Figure 5.17 below.

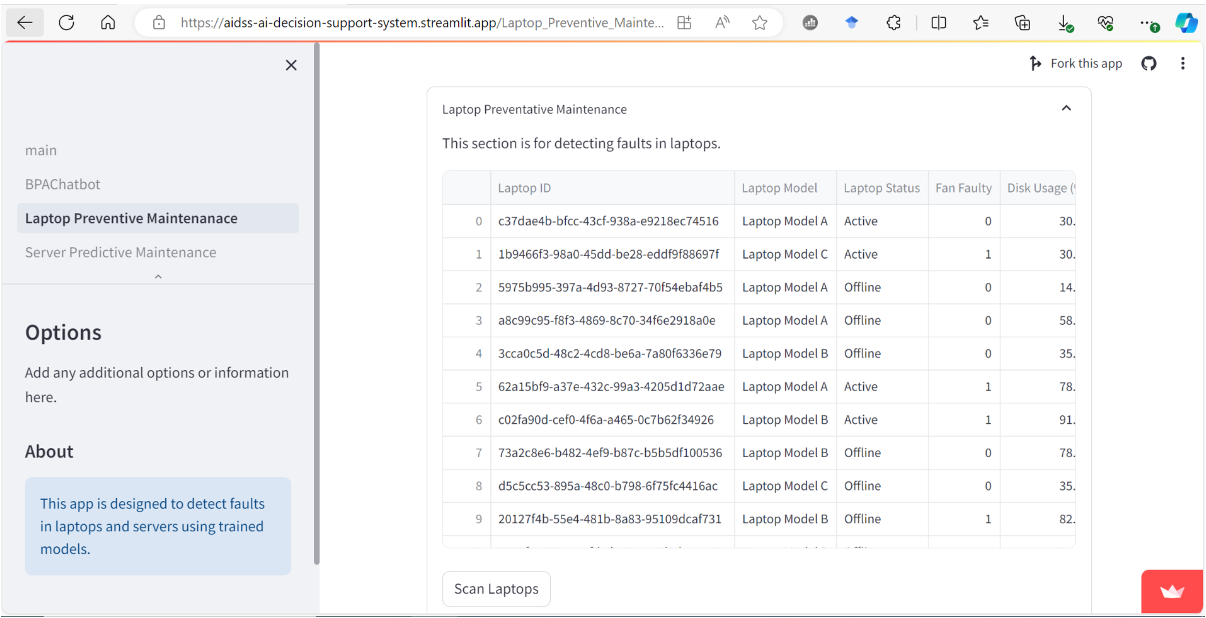


Figure 5.17 Laptop model specifications

In Figure 5.17. The fault detection area of the AIDSS for laptops encompasses both hardware and software aspects. This means that the system is designed to identify and diagnose issues related to the physical components of the laptops, such as the central processing unit (CPU), memory, hard drive, motherboard, and other hardware components. It also extends to software-related problems, including operating system errors, application crashes, driver issues, and security vulnerabilities.

By covering both hardware and software, the AIDSS ensures a comprehensive approach to fault detection, allowing it to pinpoint a wide range of problems that may affect the laptops' performance and functionality. This comprehensive coverage not only enhances the system's troubleshooting capabilities but also aids in providing holistic solutions to rectify the identified issues, thus contributing to more effective and efficient laptop maintenance and support.

Figure 5.18 Laptop model hardware

The laptop hardware and specifications (Figure 5.18) allow the system to examine datasets, discover patterns and offer insights that might otherwise go unnoticed. This method proves advantageous in IT Asset Preventative Maintenance tasks. By combining data and analytics the system can identify usage patterns, monitor performance trends and detect vulnerabilities in IT assets. This empowers maintenance measures to prevent problems before they occur.

Figure 5.19 Laptop model results

As depicted in Figure 5.19 above, when an issue, problem, or alert is detected on the laptop, it is immediately reflected in the results. Decision-makers in the ICT department then assess whether to initiate a service call and proactively reach out to the user for resolution.

iv) Fault Detection Models for Servers (Predictive Analytics)

Clicking on this icon directs users to a module dedicated to predictive analytics for both laptops and servers. The AIDSS prototype can scan the network devices to access the event logs, alerts and anomalies. The monitoring involves examining network components such as servers and switches to quickly identify any issues. With the help of analytics this approach plays a role in anticipating network glitches and minimising downtime. By analysing data, the AIDSS can predict anomalies enabling the ICT department to take proactive measures and prevent disruptions. This collaborative effort between AIDSS and predictive analytics empowers the ICT team to ensure operations by addressing network challenges highlighting the significant impact of AI on strengthening the case university's infrastructure. AIDSS can analyse data from network monitoring and management systems to identify bottlenecks and other performance issues. The results of the network scan will be presented in live mode enabling the IT team to observe outcomes as they occur. The outcomes are sent via email to the assigned individual or support desk within the ICT department for decision-making purposes. Additionally, this capability can be integrated into the call logging system, allowing the AIDSS to directly record a call within the system. This can help the ICT department optimise network performance and ensure that critical systems are running at peak efficiency.

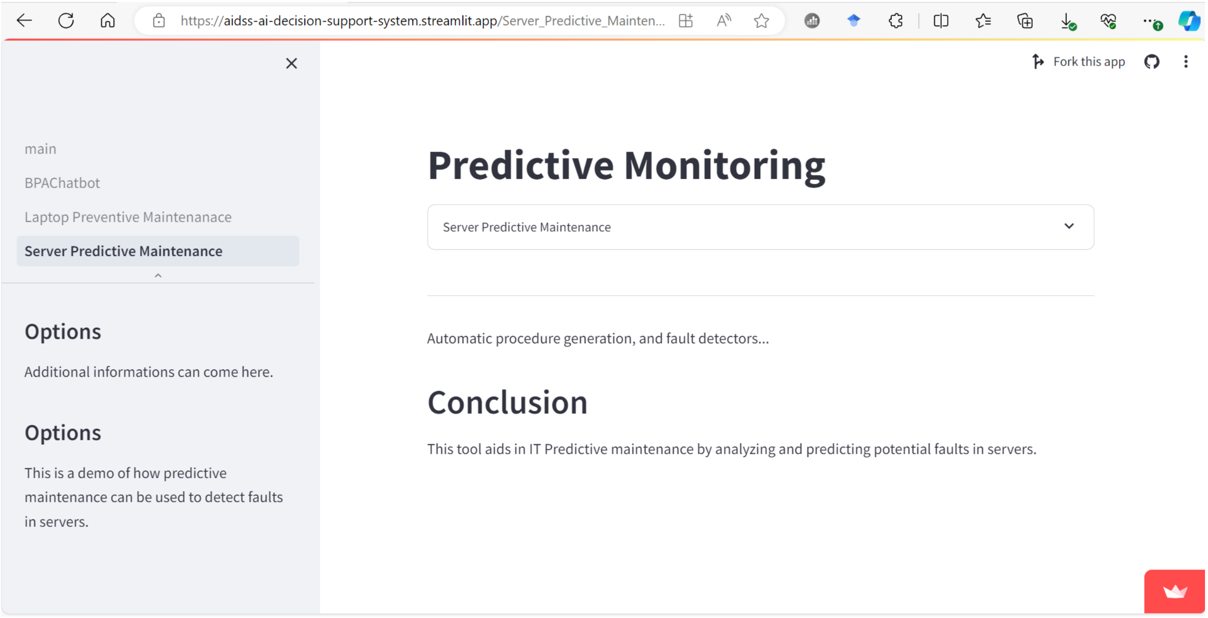


Figure 5.20 Server model for predictive analytics

In Figure 5.20 in terms of predictive analytics for network monitoring using data and advanced algorithms, network glitches and downtimes can be anticipated. This enables the ICT team to take actions and ensure operations. By combining centred insights, with analysis techniques, not only decision making is improved but also IT Operations are transformed while enhancing network stability. This approach paves a way forward in our landscape and enhances decision-making.

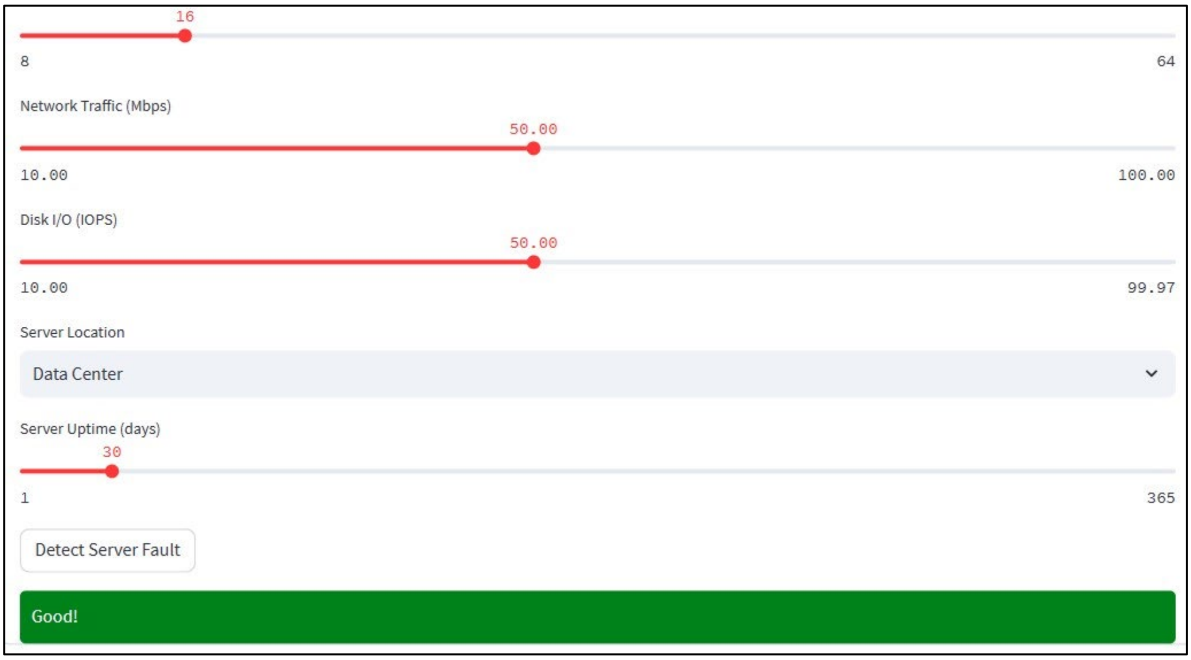


Figure 5.21 Server model results

As depicted in Figure 5.21 above, once an issue, problem or alert is detected on the server, it is mirrored in the results. Decision-makers in the ICT department then determine whether to initiate a support ticket and proactively engage to address the issue.

v) BPAChatbot

The third icon in the AIDSS leads to the BPAChatbot module, which is an interactive chatbot designed to facilitate Business Process Automation (see Figure 5.22 below).

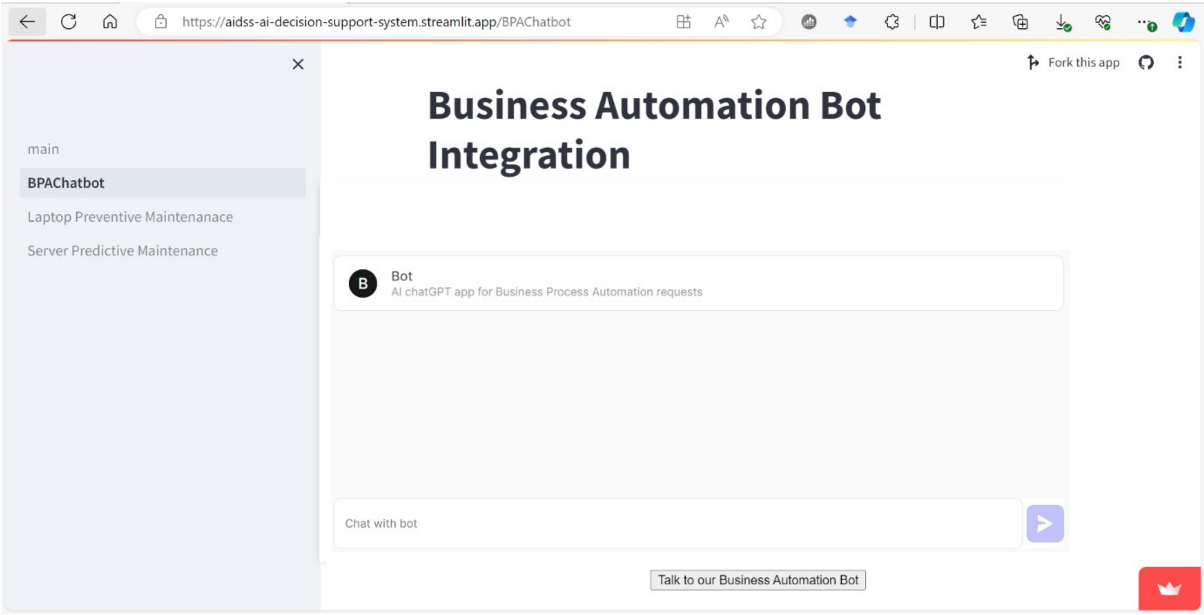


Figure 5.22 BPAChatbot integration

Users can engage with the chatbot to automate routine tasks, seek information, and streamline various operational processes. BPAChatbot acts as an intelligent assistant, providing real-time assistance and contributing to the efficiency of business processes within the system. Users can seamlessly navigate between preventative maintenance and predictive analytics to ensure proactive fault management. Additionally, the incorporation of the BPAChatbot enhances user interaction, offering a dynamic and efficient means of automating business processes within the system.

- ***Laptop Model Training and Evaluation***

Each machine learning model was meticulously trained and evaluated using the pre-processed data. Logistic Regression's interpretability, Random Forest's ensemble nature, SVC's ability to handle complex decision boundaries, and Decision Tree's simplicity were highlighted. Classification reports unveiled precision, recall, and F1-score metrics, while ROC-AUC curves visualised model performance.

- ***A Receiver Operating Characteristic (ROC) Curve:***

This curve is a crucial tool in the evaluation of binary classification models. It provides a comprehensive view of how well a model can differentiate between two classes, typically a positive class (e.g., presence of an illness) and a negative class (e.g., absence of a disease). Let's delve deeper into the key components and concepts associated with ROC curves:

- ***Sensitivity (True Positive Rate - TPR):***

Sensitivity measures the model's ability to correctly identify instances of the positive class. It represents the proportion of true positives (correctly identified positives) out of all actual positives. In medical contexts, high sensitivity is essential as it ensures that actual cases of a condition are not missed.

- ***False Positive Rate (FPR):***

FPR measures how often the model incorrectly predicts the positive class when the true class is negative. It is calculated as the proportion of false positives (incorrectly identified positives) out of all actual negatives. Minimising the FPR is crucial in scenarios where false alarms are costly or undesirable.

- ***Random Classifier Line:***

The diagonal line from the bottom-left to the top-right on the ROC graph represents the performance of a classifier that makes predictions randomly. This line serves as a baseline, and any classifier performing worse than this is considered ineffective.

- ***Ideal Classifier Line:***

The ideal classifier line is a vertical line along the left edge of the ROC graph. It signifies a perfect classifier that achieves a TPR of 1 (100% sensitivity) while maintaining an FPR of 0 (no false positives). Achieving this ideal scenario is rare in practice, but it sets the benchmark for model performance.

- ***Model's ROC Curve:***

The ROC curve generated by your model showcases its discriminatory power across different decision thresholds. The curve illustrates how the model's sensitivity and specificity (1 - FPR) change as you adjust the classification threshold. A model is deemed more accurate when its ROC curve is closer to the ideal classifier line and further away from the random classifier line.

- ***Area Under the Curve (AUC):***

AUC is a summary metric that quantifies the overall performance of the ROC curve. It calculates the area under the ROC curve, and a value greater than 0.5 indicates that the model performs better than random chance. A higher AUC suggests a more effective classifier, with a perfect classifier having an AUC of 1.The plots below show the models’ performance.

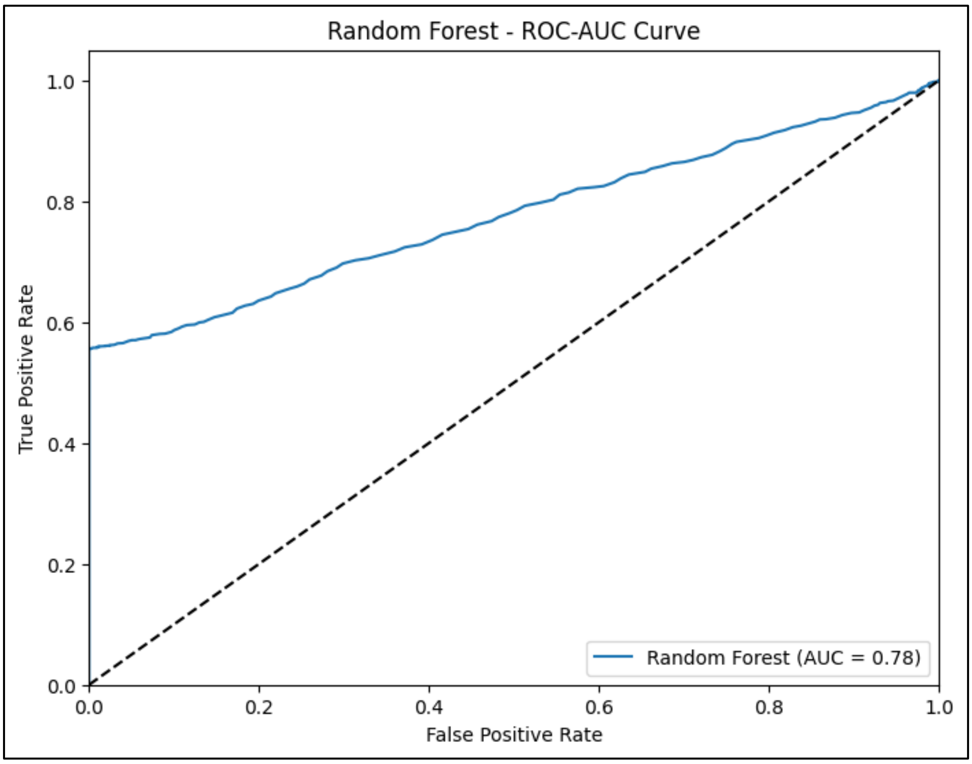


Figure 5.23 Laptop model random forest

In Figure 5.23, ROC curves provide a valuable visual representation of a binary classification model's ability to distinguish between classes. By examining the curve and calculating the AUC, one can gain insights into the model's performance. A model with a ROC curve closer to the ideal line and an AUC greater than 0.5 is indicative of better predictive power, making it a strong candidate for tasks where class differentiation is critical. The ROC curves presented in the plots below allow for direct comparison the performance of different models, aiding in model selection and optimisation.

```
rf = RandomForestClassifier(random_state=42)
rf.fit(X_train_laptops, y_train_laptops)

rf_pred = rf.predict(X_test_laptops)
print(classification_report(y_test_laptops, rf_pred))
```

```
              precision    recall  f1-score   support

           0       0.51      0.45      0.48       948
           1       0.76      0.80      0.78      2052

    accuracy                           0.69      3000
   macro avg       0.63      0.62      0.63      3000
weighted avg       0.68      0.69      0.68      3000
```

```
# The best model is Catboost Classifier model
import joblib

# Save the model to a file
joblib.dump(rf, 'laptop_model.joblib')
```

```
['laptop_model.joblib']
```

Figure 5.24 Laptop model random

The random forest model (Figure 5.24) emerged as the most effective. It was designated as the optimal model and subsequently employed for cloud deployment.

vi) Server Model Training and Evaluation

The server fault detection models paralleled the laptop models in training and evaluation. The versatility of Logistic Regression, Random Forest's robustness, SVC's ability to handle complex relationships, and Decision Tree's interpretability were all interrogated. Classification reports and ROC-AUC curves offered insight into model accuracy and performance. The models' performance is displayed below.

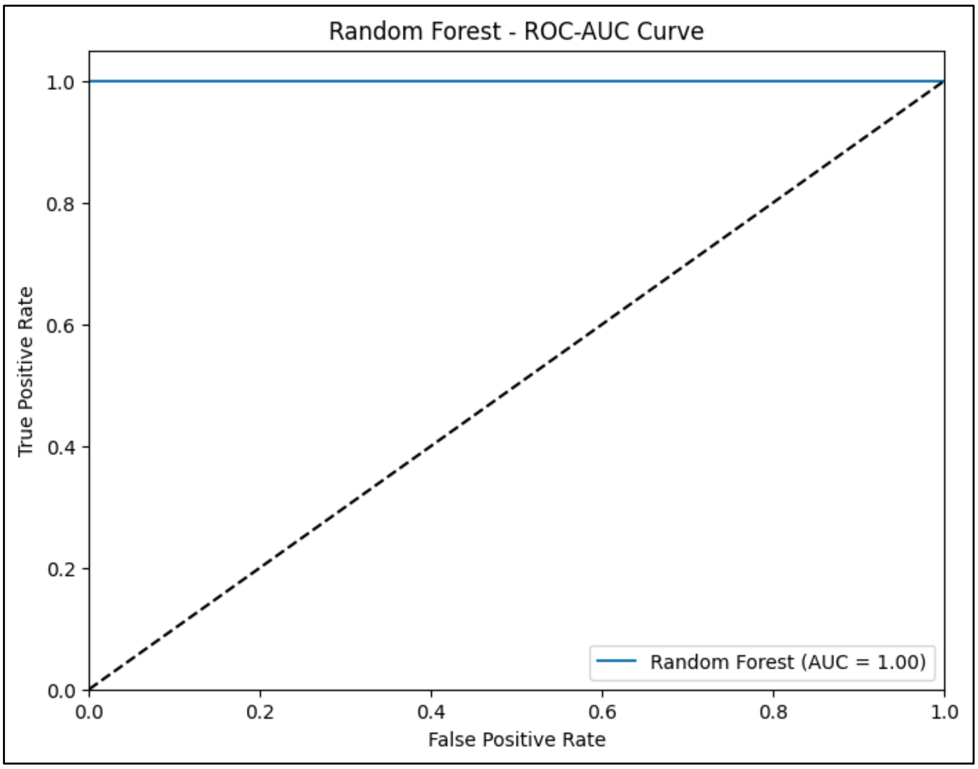


Figure 5.25 Server model random forest

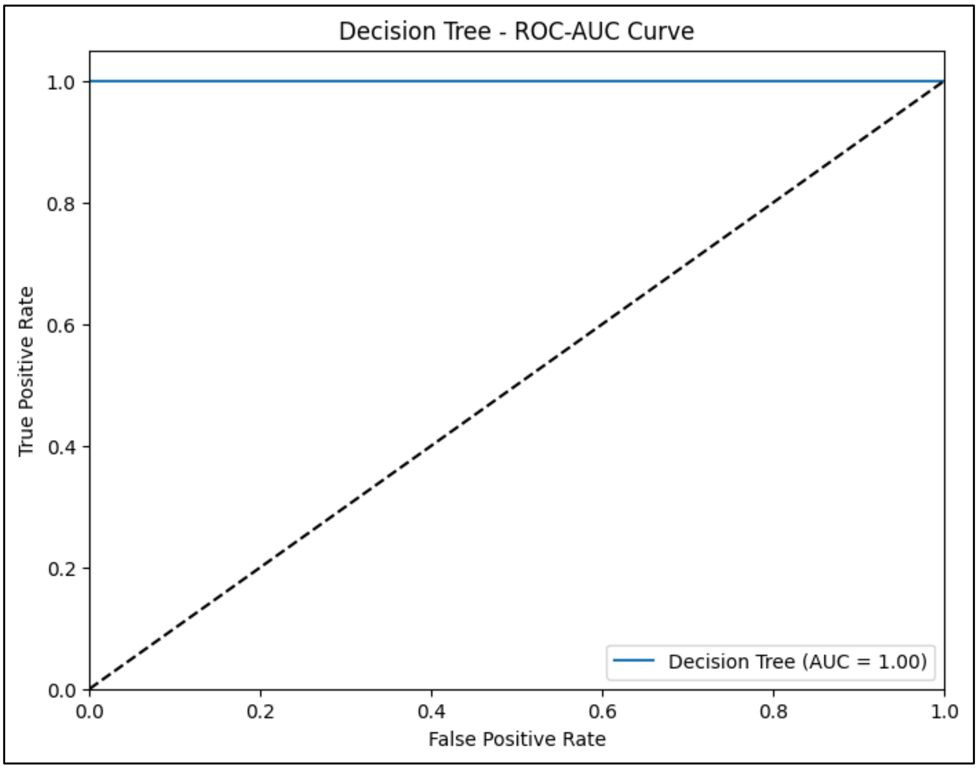


Figure 5.26 Server model decision tree

It is evident that both the Random Forest Classifier (Figure 5.25) and the Decision Tree Classifier (Figure 5.26) are strong contenders for being considered good models, as they achieved a flawless accuracy rate of 100%.

The AIDSS intention is to enhance the flexibility, scalability and adaptability of IT Operations, leading to better decision-making within the ICT department. This marks a shift from conventional IT service structures to offer services promptly, effectively and at a heightened quality level. This transformation serves as a foundation for integrating contemporary technologies such as AI, known for its capacity to enhance and enrich user experiences in IT service and operations management, thereby actively refining organisational functions in real-time. Making timely decisions could lead to enhanced service delivery and greater efficiency thanks to the standardisation and automation of operations. The AIDSS can also be used to support decision-makers in their tasks. For example, the system could provide a dashboard that displays key performance indicators (KPIs) for the ICT department. The dashboard could also be used to track the progress of tasks and to identify any potential problems. Overall, the AIDSS can be a valuable tool for the ICT department. The system can help the ICT department make better decisions, improve its efficiency and achieve its goals.

5.5 Chapter Summary

The study successfully achieved its aim, and Chapter seven provides a detailed account of the contributions made by this research. This study conducted interviews to grasp participant experiences and needs. Ten interviews with ICT decision-makers provided insights. Interview findings align with existing literature, reinforcing the significance of AI in strategic planning and operational efficiency. AI is seen as essential for preventative maintenance, enhancing network monitoring, and automating processes.

This chapter encapsulated the successful development and implementation of an AI application designed for fault detection and student query assistance. The fault detection models enhance system reliability and uptime, contributing to operational efficiency. The BPAChatBot transforms communication, providing prompt and contextually relevant responses thereby enhancing the BPA request experience. The AI application explored in this report represents a convergence of technology and IT operations in the ICT department. The fault detection models contribute to the sustainability of technological infrastructure, minimising disruptions and optimising system performance. Both aspects underscore the transformative potential of AI in the higher education context. The effective utilisation of monitoring tools, event logs and alerts greatly influence the capabilities of an artificial intelligence-enabled decision support system to support operational decision-making within the ICT department at the university. Through incorporating data from relevant data sources, the AIDSS obtains time and historical insights into the IT environment of the university. Consequently, this significantly impacts decision making processes. The AIDSS can detect issues in advance by monitoring and can predict potential bottlenecks. It can also quickly identify the root causes of incidents resulting in resolution. Additionally with access to data the system can provide analytics that help anticipate performance fluctuations and resource requirements. These insights not only optimise how resources are allocated but also support data driven decision making allowing in the ICT department to make choices that improve efficiency and operational excellence ultimately enhancing overall decision-making processes.

Chapter six presents the findings from a questionnaire designed to assess the AIDSS's performance, effectiveness, and user satisfaction. The survey involved ICT decision-makers and included various key performance indicators, such as response time, predictive analytics accuracy, user interface and overall user experience. These insights provided a well-rounded understanding of the AIDSS's impact and usability.

CHAPTER 6 : ANALYSIS AND FINDINGS

6.1 Introduction

The preceding chapter focused on designing and developing the AIDSS artefact, which involved utilising data gathered through interviews to identify the problem and set objectives for the solution. Additionally, the chapter provided an overview of the artefact's features. Presented in this chapter are the findings from the designed questionnaire, which served as an evaluation tool to gauge the performance, effectiveness and user satisfaction of the AIDSS. The evaluation process involved inviting decision-makers from the ICT department to participate in the survey. The questionnaire was adapted from Kao *et al.*, (2016) and constructed with additional questions based on the Goal Question Metric (GQM) approach, encompassing a comprehensive set of key performance indicators. These indicators included measuring the system's response time, the accuracy of its predictive analytics, the intuitiveness of the user interface, and the overall user experience. The responses from the participants provided valuable insights into how the system performed and how satisfied users were with its functionalities. By incorporating a diverse range of indicators, the questionnaire allowed for a holistic assessment of the AIDSS artefact's capabilities, contributing to a well-rounded understanding of its impact and usability within the ICT department. Please refer to Appendix H reports all SPSS outcomes associated with questionnaire responses provided by the twenty-eight participants.

6.2 Evaluation of the Artefact

The study involved an evaluation of the AIDSS prototype artefact using the Goal Question Metric (GQM) approach. GQM is a structured and systematic method that allows researchers to set specific goals, formulate relevant questions, and develop appropriate metrics to measure the success of those goals (Koziolek, 2008).

This evaluation process provided valuable insights into the effectiveness and performance of the AIDSS prototype, helping to identify areas of improvement and further development. During the evaluation phase, the researchers established clear objectives for the AIDSS prototype and formulated specific questions to address the system's functionality, usability, and overall performance. They carefully selected appropriate metrics and indicators to quantitatively assess the system's performance against the predefined goals. This approach ensured that the evaluation process was well-structured, objective, and focused on obtaining meaningful and actionable results. The researcher made use of questionnaires as a data collection method to evaluate the artefact. The questionnaires were structured in a way that is relative to the experience of the participants and their receptiveness of AIDSS. The questionnaire had closed ended questions which allowed the employees to select a box that had an answer that they agreed with. Demographic data was collected to test if the participants' experience is influenced by factors such as age, gender and work experience (Michelle, 2020).

6.2.1 Questionnaire data analysis

In this study, the developed artefact underwent testing and evaluation using a questionnaire to assess its alignment with user requirements. Thirty questionnaires were distributed online to ICT department personnel, resulting in Twenty-eight responses. The collected data was recorded in online and analysed using SPSS version 26. Adhering to the DSR methodology, any deficiencies in the system were refined until they met user expectations. Evaluation of the artefact was carried out as discussed in this chapter. Table 6.1 below illustrates a typical questionnaire item example that was utilised in this study, it contained an option of 5 possible Likert scale responses expected from the participants.

Table 6.1 Example of questionnaire items

LIKERT SCALE QUESTIONNAIRE ITEMS Choose the **BEST** option, for each item	**SD**	**D**	**N**	**A**	**SA**
I can always rely on the university’s ICT system					

Note: SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree

For ease of reference refer to Appendix F for a list of questions pertaining to the research questionnaire for this study. By employing a systematic and data-driven evaluation approach, the researcher ensured that the developed AIDSS artefact was not only aligned with the department's requirements but also effective in enhancing decision-making processes, thus contributing to the overall efficiency and success of the university's ICT operations.

6.2.2 Goal Question Metric

The Goal Question Metric (GQM) (Appendix G) approach is a methodical methodology that is used to assess the efficiency of a research project or an artefact (Koziolek, 2008). It offers a systematic framework for setting clear objectives, formulating relevant questions, and choosing acceptable metrics so that data may be interpreted in an objective manner. The GQM approach fosters learning and improvement—what we learn from one initiative informs us about what to do differently or better with the next. The goal is to use the GQM process to understand why you sought to do something (i.e.: what the initiative's objective was) and how it achieved its goals (the outcome).The GQM methodology will be used in the context of the AI-enabled decision support system for higher education institutions in South Africa. This will be done to evaluate the degree to which there has been an improvement in the operational decision-making process at the ICT department.

Conceptual Level - Defining Goals

At the conceptual level, the general objectives of the research project need to be outlined in a clear and concise manner. In the context of this investigation, the major objective is to create an AI-enabled decision support system with the purpose of enhancing decision-making processes inside higher education institutions in South Africa, with a specific emphasis on the operations of ICT departments. "Improve operational decision-making at the ICT department through the implementation of an AI-enabled decision support system."

Operational Level - Developing Questions

The following phase is to create a collection of questions pertaining to the item under research, which is the AI-enabled decision support system, after the conceptual objectives have been defined. These inquiries must be pertinent to the overarching objective of enhancing the ICT department's ability to make decisions. Following are some operational queries related to the study's goals:

- How does the AI-enabled decision support system affect the effectiveness of allocating ICT resources?
- Does the system's integration of various data sources result in the ICT department making more data-driven decisions?
- How satisfied are users with the user interface and how simple it is for decision-makers to utilise the system?

- In what ways do the system's predictive analytics help the ICT department detect future problems?
- How do decision-makers evaluate the reliability and validity of the system's recommendations?

These operational queries focus on certain facets of the AI-enabled decision support system and how it affects the decision-making process of the ICT department.

Quantitative Level - Defining Metrics

At the quantitative level, the datasets are collected that are necessary to objectively answer the operational issues and quantify the performance of the AI-enabled decision support system. This is done in preparation for the next level of analysis, which is the quantitative level. The performance of the system is evaluated quantitatively using the metrics that have been set. To respond to the above stated questions using measurable methods, the researcher defined a set of twenty-five metrics corresponding to the five operational level questions.

Presented on the Table 6.2 below are the key aspects of interest for each of these formulated questions. Subsequently, these focal points within the prototype were transformed into statements (Likert scale), which ICT personnel evaluated by assigning ratings on a scale.

Table 6.2 AIDSS Artefact Quantitative Goal Question Metrics

Code	Metric	Weighted Statements
*M*1	Efficiency	The system is easy to use
*M*2	Efficiency	The system helps me make decisions efficiently
*M*3	Efficiency	The system helps me make decisions quickly
*M*4	Efficiency	The system helps me make decisions effectively
*M*5	Efficiency	The system interface is easy to use
*M*6	User Satisfaction	System integrates existing decision-making processes or tools
*M*7	Scalability	I am comfortable with the data being collected and stored by the system for decision-making purposes
*M*8	User Satisfaction	The system complemented the skills and expertise of ICT personnel
*M*9	User Satisfaction	I believe I have learned how to operate the system

Code	Metric	Weighted Statements
*M*10	Integration	The system provides appropriate error messages and clear instructions of how to address errors
*M*11	Integration	The system improved optimisation of resource allocation
*M*12	Integration	The system minimised resource wastage
*M*13	Decision Support System	I am satisfied with the system's speed and responsiveness
*M*14	Scalability	The system provides information that helps me make decisions effectively
*M*15	Scalability	The system assists me in my day-to-day tasks and responsibilities
*M*16	Decision Support System	System's early detection of potential problems through predictive analytics positively impacted ICT operations
*M*17	Decision Support System	System successfully predicted and prevented impending ICT issues before they escalated
*M*18	Decision Support System	I have confidence in the system's predictive analytics for detecting potential future problems within the ICT operations
*M*19	Scalability	The system provides easily understood information
*M*20	Scalability	The system's chat feature assists me to make decisions
*M*21	User Satisfaction	The system has improved the quality of my decision-making process
*M*22	Scalability	I would recommend the system to others for decision-making purposes
*M*23	Scalability	The system had all expected functions and abilities
*M*24	Efficiency	Overall, the system is easy to use
*M*25	Efficiency	Overall, I am satisfied with the system

These quantitative metrics provide concrete indications of the system's influence on the operational decisions made within the ICT department, which may be gleaned from the data collected.

The process began with the researcher guiding the employee through the artefact, providing a comprehensive understanding of its functionalities and features. Afterward, the employees proceeded to complete the questionnaire, expressing their opinions and assessments based on their experience with the artefact. Furthermore, the researcher availed himself to address any additional questions or feedback that the employees might have had during the evaluation. This approach allowed for a thorough and interactive assessment, ensuring that the ICT department employees' perspectives were effectively captured and contributing to the overall reliability and validity of the study's findings.

The visual representation depicted in Figure 6.1 below offers a clear and structured depiction of how the goal, questions and metrics seamlessly interconnect to construct the GQM model for the study. This model effectively links the overarching aim of the study—centred around the development of an AI-enabled decision support system—with specific and targeted questions and measurable metrics. This structured alignment facilitates a systematic and insightful approach to evaluating the system's performance and efficacy in the ICT department of the case university. The defined goal acts as a guiding beacon for the subsequent formulation of pertinent questions, each tailored to delve into specific facets of the system's functionality and its impact within the intended problem. Subsequently, attention is given to the formulation of twenty-five metrics using 5-lickert scale, quantifying the outcomes of the evaluation process.

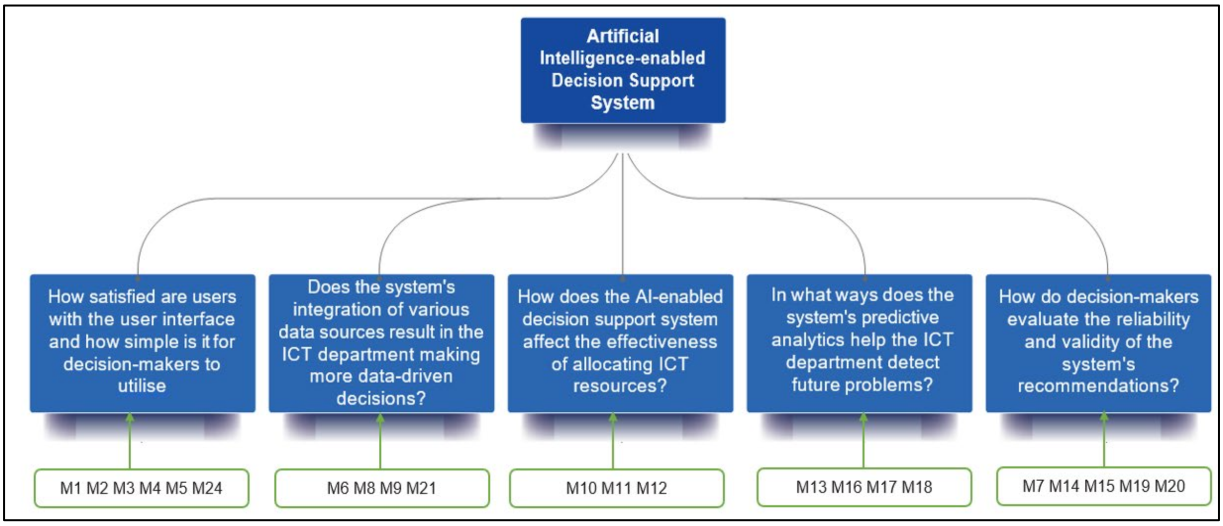


Figure 6.1 Goal Question Metric for evaluation

A total of twenty-five questions were devised to delineate the areas of study, aligning with the overall objectives as stated in the methodology chapter. Twenty-eight staff members from the ICT department, comprising both male and female respondents, participated in the questionnaire. The questions, along with biographical details (Appendix F), designed to elicit responses addressed the operational level questions of the GQM framework and affirm the practicability of the artefact. The primary data source analysed for this research was the responses to the questionnaire, which contained valuable information. Additionally, comments and observations also contributed to the data. Therefore, this study incorporates the writer's personal insights, which were gained through spending time in the setting. As part of the research process, the researcher visited the ICT department to conduct site observations.

6.2.3 Questionnaire Response Rate

A set of 25 questions were crafted that cover both biographical details and artefact related questions to explore the research questions. The questionnaires were distributed among IT staff members—both males and females—with a total of 30 questionnaires handed out. Ultimately 28 IT staff members participated in the study resulting in a response rate of 93.33%. It is worth mentioning that all returned questionnaires were considered valid. The questionnaire served as the source for data analysis.

6.3 Descriptive Statistics

Descriptive Statistics play a role in presenting and explaining the characteristics of the data collected in a way that is easy to understand for the intended audience (Ali *et al.*, 2019). In this study descriptive statistics included frequencies, customised tables, means and standard deviations. To highlight the findings, tables and graphs represent variables such as gender, age, job position, length of service within the organisation and educational level.

6.3.1 Gender

The gender distribution of the participants presented in Table 6.3 shows that 6 (21.4%) participants were females and 22 (78.6%) were males.

Table 6.3 Gender Distribution

Gender	Frequency	%
Female	6	21.4
Male	22	78.6

Total	28	100

Figure 6.2 shows a graphical view of gender distribution by participants.

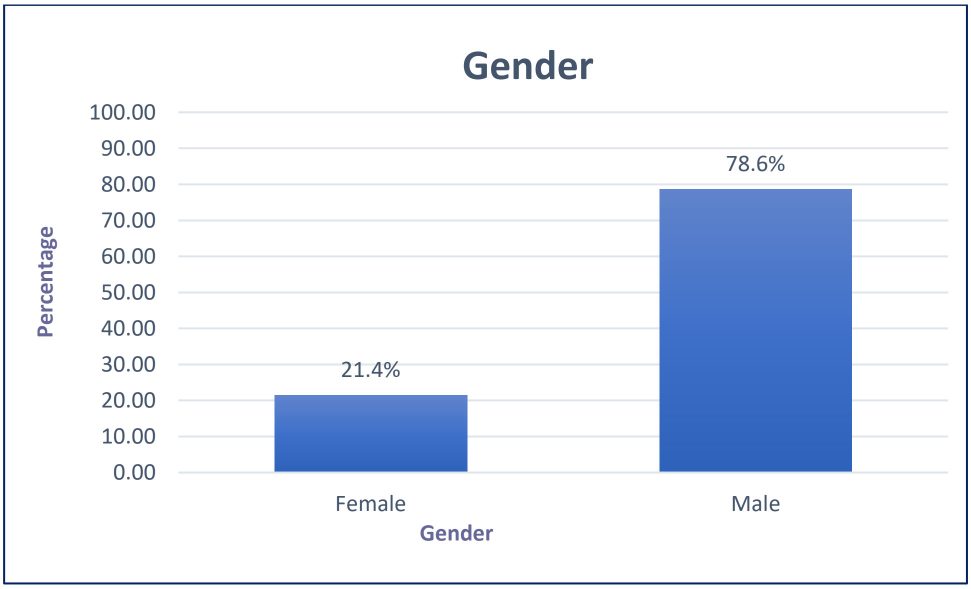


Figure 6.2 Gender distribution of participants

6.3.2 Age

Table 6.4 classifies the participants by age group. The age frequency distribution indicates that 7.1% (n=2) of the participants fall within the age group of 18-28 years, 57.1% (n=16) within the age group of 29-39. It also shows that 28.6% of the participants (n=8) fall within the age group 40-49 years while 7.1% of the participants (n=2) are within the age group 50-59 years. The table illustrates that a significant majority, approximately 92.86% of the participants fall within the younger age bracket, ranging from 18 to 49 years old. In contrast, a smaller proportion, constituting 7.14% of the participants belong to the older age group.

Table 6.4 Age Distribution

Age	Frequency	%
18-28 years	2	7.1
29-39 years	16	57.1
40-49 years	8	28.6

50-59 years	2	7.1
Total	28	100

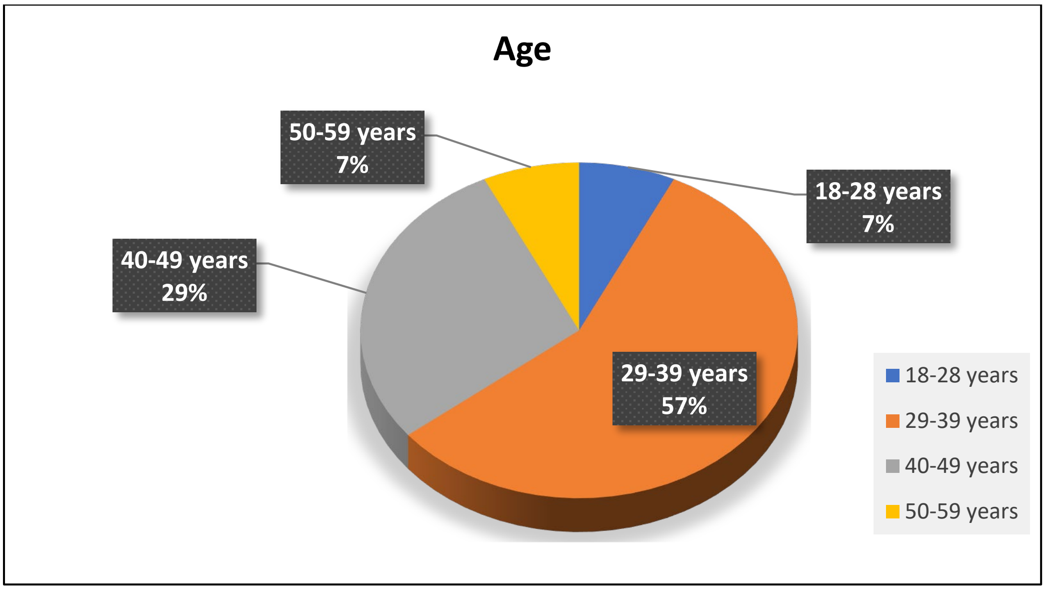


Figure 6.3 Age distribution of the participants

Figure 6.3 provides a visual representation of the distribution of participants by age.

6.3.3 Position

Table 6.5 below indicates the position the participants hold in the ICT department of the selected university The majority of the participants, 42.9% (n=12), are technical staff, followed by 25% (n=7) supervisors and 25% (n=7) are management. While only 7.1% (n=2) are employed in administration position. Overall, approximately 50% of the participants hold positions at the supervisor or manager level within the selected university. This indicates that most of the participants possess a significant level of experience.

Table 6.5 Employment Positions

Position	Frequency	%
Admin Staff	2	7.1
Technical Staff	12	42.9

Supervisor	7	25.0
Manager	7	25.0
Total	28	100

6.3.4 Years in organisation

Table 6.6 shows the length of the period served by the participants in the institution. Most of the employees (28.6% or n=8) have been in working in the selected university for nine years and more which indicates that they are quite familiar with the IT operations at this HEI. Six participants (21.4%) have worked there for six years but less than eight years, while 25% (n=7) have worked there for three to five years, like 25% who have worked there for seven months and less than two years. This suggests that a substantial portion of the participants have a considerable background or knowledge of the case university.

Table 6.6 Years in Organisation

Years	Frequency	%
7 months-2 years	7	25.0
3-5 years	7	25.0
6-8 years	6	21.4
9 years or more	8	28.6
Total	28	100

6.3.5 Study level

Table 6.7 demonstrates the level of education of the sample population. The participants are IT professionals at the selected university with qualifications ranging from undergraduate degree as well as bachelor’s and master’s degrees. Most of the participants or 42.9% (n=12) have undergraduate qualifications, 35.7% (n=10) have honours degree and 21.4% (n=6) have master’s degree. In general, 57.14% of the participants hold Honours or Masters degrees, while the remaining participants have undergraduate qualifications.

Table 6.7 Study Level

Level	Frequency	Valid %
Undergraduate	12	42.9
Honours	10	35.7
Masters	6	21.4
Total	28	100

6.4 Variables

The researcher used dependent (decision support) and independent variables (user satisfaction, efficiency, integration, scalability) in the study to measure how participants viewed and experienced the prototype AIDSS. Through the variables, the researcher was able to examine responses and explore how each factor influenced participants opinions and satisfaction levels. The data aligning with the research goals and providing a comprehensive understanding of how participants perceived the impact of AIDSS. The analysis and discussion of the questionnaire's results assess the extent to which each AIDSS construct influenced IT staff satisfaction in the context of the case university. The assessment of response strength was conducted on a 5-point Likert scale where 1 signified strongly disagree, 2 signified disagree, 3 is for neutral, 4 signalled agree and 5 represented strongly agree. This methodology allows for a clear understanding of the participants' sentiments and alignment with the provided statements. The participants' responses to the attitude statements are found in the following section.

6.4.1 Decision Support

This construct relates to the GQM framework in response to the question: *How do decision-makers evaluate the reliability and validity of the system's recommendations*?. In Table 6.8, the findings reveal that the statement "I would recommend the system to others for decision-making purposes " received the highest percentage of agreement at 64.3%. It was closely followed by the statement "The system had all expected functions and abilities," with 53.6% agreement. Additionally, the statement "The system provides information that helps me make decisions effectively " garnered a 50.0% agreement rate. In examining the respondents' perceptions of various system-related statements, notable patterns emerged. For the statement "I am comfortable with the data being collected and stored by the system for decision-making purposes," responses were distributed across the spectrum, with a significant portion being in the neutral category with 28.6%. However, a considerable percentage of respondents expressed strong agreement with 35.7% and 28.6%, indicating comfort with data collection and storage. Regarding the statement "The system assists me in my day-to-day tasks and responsibilities," a substantial majority either agreed (46.4%) or strongly agreed (39.3%), underlining the system's perceived usefulness in daily work. Conversely, a smaller fraction disagreed (7.1%) or remained neutral (7.1%) on this matter. Regarding the item "The system provides easily understood information," respondents' perceptions were diverse. Approximately 7.1% disagreed with the statement, while 25.0% were neutral. On the positive side, 32.1% agreed, and a substantial portion, accounting for 35.7%, strongly agreed. These responses indicate a mix of opinions, with a notable proportion of respondents finding the prototype's information easily comprehensible, but also highlighting areas where clarity may need improvement. Lastly, in relation to the item "The system's chat feature assists me in making decisions," respondents displayed a balanced distribution across the categories, with a notable portion agreeing (35.7%) or strongly agreeing (35.7%) with the statement. However, a smaller percentage disagreed (14.3%) or remained neutral (14.3%).

Table 6.8 Decision Support

Items		SD	D	N	A	SA
I am comfortable with the data being collected and stored by the system for decision-making purposes.		1	1	8	8	10
		3,6%	3,6%	28,6%	28,6%	35,7%
The system provides information that helps me make decisions effectively.		0	1	8	14	5
		0,0%	3,6%	28,6%	50,0%	17,9%
The system assists me in my day-to-day tasks and responsibilities.		0	2	2	13	11
		0,0%	7,1%	7,1%	46,4%	39,3%
The system provides easily understood information.		0	2	7	9	10
		0,0%	7,1%	25,0%	32,1%	35,7%
The system's chat feature assists me to make decisions.		0	4	4	10	10
		0,0%	14,3%	14,3%	35,7%	35,7%
I would recommend the system to others for decision-making purposes.		0	1	4	18	5
		0,0%	3,6%	14,3%	64,3%	17,9%
The system had all expected functions and abilities.		1	4	6	15	2
		3,6%	14,3%	21,4%	53,6%	7,1%

Note: SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree

The high percentage of agreement with statements such as "I would recommend the system to others for decision-making purposes," "The system had all expected functions and abilities," and "The system provides information that helps me make decisions effectively" indicates a positive perception of the system's reliability and effectiveness. Additionally, the significant percentage of respondents expressing comfort with data collection and storage suggests a level of trust in the system's ability to handle data securely. Furthermore, the strong agreement with statements affirming the system's usefulness in day-to-day tasks and responsibilities underscores its perceived reliability in practical scenarios. However, the diverse responses regarding the system's provision of easily understood information and the chat feature's assistance in decision-making highlight areas where the system's validity may need further evaluation and improvement. Therefore, the balanced distribution of responses across various statements reflects a firm assessment of the system's reliability and validity by decision-makers, with both positive perceptions and areas for potential enhancement identified.

6.4.2 Efficiency

Efficiency connects to the GQM framework, addressing the question: *How does the AI-enabled decision support system affect the effectiveness of allocating ICT resources*? As per Table 6.9 in response to the items whether “The system provides appropriate error messages and clear instructions of how to address errors,” the data reveals that 17.9% of the total participants strongly agree. Additionally, 39.3% of participants expressed neutrality, 25.0% indicated agreement, and 7.1% strongly disagreed with this statement. These results illustrate a range of attitudes among participants regarding the artefact’s error messaging and guidance, with a sizable portion holding a neutral stance. In response to whether “The system improved the optimisation of resource allocation”, the data reveals that 21.4% of the total participants strongly agree with this statement, indicating a high level of support. Furthermore, 60.7% expressed agreement, 10.7% held a neutral perspective, and 7.1% disagreed with this assertion. These findings suggest that a substantial majority of respondents perceive the system as contributing positively to resource allocation optimisation, although there is a minority with reservations.

Table 6.9 Efficiency

Items	SD	D	N	A	SA
The system provides appropriate error messages and clear instructions of how to address errors	2	3	11	7	5
	7,1%	10,7%	39,3%	25,0%	17,9%
The system improved optimisation of resource allocation	0	2	3	17	6
	0,0%	7,1%	10,7%	60,7%	21,4%
The system minimised resource wastage	0	1	4	15	8
	0,0%	3,6%	14,3%	53,6%	28,6%

Note: SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree

On the examination whether “The system minimised resource wastage”, the results indicate that 28.6% of the total participants strongly agree with this statement, demonstrating strong support for the system's efficiency in resource management. Additionally, 53.6% agree with the statement, 14.3% are neutral in their stance, and 3.6% disagree with the assertion. These findings suggest a noteworthy consensus among respondents regarding the system's effectiveness in minimising resource wastage, with a majority expressing agreement. These insights shed light on the perceived impact of the artefact on resource allocation and efficiency within the context under examination.

6.4.3 Integration

This construct corresponds to the GQM framework when addressing the question: *Does the system's integration of various data sources result in the ICT department making more data-driven decisions*?. Table 6.10 item which assesses whether “The system integrates existing decision-making processes or tools”, the data reveals that 25.0% of the total participants strongly agree, 35.7% agree, 3.6% of the participants disagree and 10.7% strongly disagree. In terms of evaluating whether “The system complemented the skills and expertise of ICT personnel”, 35.7% of participants strongly agree, 46.4% agree, 14.3% are neutral and 3.6% disagree. These results indicate a significant consensus among respondents regarding the artefact's role in enhancing the skills and expertise of ICT personnel, with a majority expressing agreement. These insights provide valuable information about how the artefact interacts with existing processes and personnel expertise within the context of the study.

Table 6.10 Integration

Items	SD	D	N	A	SA
System integrates existing decision-making processes or tools.	10,7%	3,6%	25,0%	35,7%	25,0%
	0	1	4	13	10
The system complemented the skills and expertise of ICT personnel.	0,0%	3,6%	14,3%	46,4%	35,7%
	0	1	6	8	13
I believe I have learned how to operate the system.	0,0%	3,6%	21,4%	28,6%	46,4%
	10,7%	3,6%	25,0%	35,7%	25,0%
I would recommend the system to others for decision-making purposes.	0	1	9	12	6
	0,0%	3,6%	32,1%	42,9%	21,4%

Note: SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree

On evaluating the statement "I believe I have learned how to operate the system", 46.4% of participants strongly agree, 28.6% agree, 21.4% are neutral and 3.6% disagree. In response to the statement, "I would recommend the system to others for decision-making purposes", 3.6% participants disagree, 32.1% are neutral on the matter, 42.9% agree while 21.4% strongly agree. These responses suggest varying levels of acceptance and reservations among participants regarding the artefact's ability to seamlessly integrate with existing decision-making processes and tools.

6.4.4 User Satisfaction

This construct corresponds to the GQM framework, addressing the question: *How satisfied are users with the user interface and how simple it is for decision-makers to utilise the system*?. Table 6.11, assessing whether "The system is easy to use", 21.4% of the total participants strongly expressed their comfort and ease with the system, while 53.6% indicated agreement, and 25.0% are neutral. For the next item, 21.4% of participants strongly agreed that the system significantly contributes to efficient decision-making, with 60.7% in agreement and 17.9% remaining neutral. As for the item statement system facilitates quick decision-making, 32.1% of participants strongly agreed, while 42.9% agreed, and 25.0% were neutral. In the case of the statement which gauges the overall opinion, 3.6% strongly disagreed with the statement that the system is easy to use, 7.1% disagreed, 10.7% remained neutral, 50.0% agreed, and 28.6% strongly agreed. For the last item, 25.0% of participants strongly agreed that they are satisfied with the system, with 53.6% in agreement, 17.9% neutral, and 3.6% expressing disagreement. These responses reflect a diverse range of opinions and perceptions among participants regarding the artefact's usability, efficiency and overall satisfaction. The significant portion of participants expressed satisfaction with the user interface's simplicity and utility for decision-makers, though some uncertainty and dissatisfaction exist among a minority of participants.

Table 6.11 User Satisfaction

Items	SD	D	N	A	SA
The system is easy to use.	0	0	7	15	6
	0,0%	0,0%	25,0%	53,6%	21,4%
The system helps me make decisions efficiently.	0	0	5	17	6
	0,0%	0,0%	17,9%	60,7%	21,4%
The system helps me make decisions quickly.	0	0	7	12	9
	0,0%	0,0%	25,0%	42,9%	32,1%
The system helps me make decisions effectively.	0	0	8	18	2
	0,0%	0,0%	28,6%	64,3%	7,1%
The system interface is easy to use.	0	0	9	14	5
	0,0%	0,0%	32,1%	50,0%	17,9%
Overall, the system is easy to use.	1	2	3	14	8
	3,6%	7,1%	10,7%	50,0%	28,6%
Overall, I am satisfied with the system.	0	1	5	15	7
	0,0%	3,6%	17,9%	53,6%	25,0%

Note: SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree

6.4.5 Scalability

This construct relates to the GQM framework in response to the question: *In what ways does the system's predictive analytics help the ICT department detect future problems*? As depicted in Table 6.12, 35.7% of the participants strongly supported the statement satisfied with the system's speed and responsiveness, and 50% agreed, while 14.3% were neutral, indicating a high level of agreement. Similarly, strong agreement was observed for the item system's early detection of potential problems through predictive analytics positively impacted ICT operations, with 28.6% of respondents strongly supporting this notion, 53.6% agreed, 14.3% were neutral while 3,6% disagreed. Furthermore, a significant portion (32.1%) of the participants strongly supported the statement system successfully predicted and prevented impending ICT issues before they escalated. With 50% also agreeing and 21.4% neutral. For the statement I have confidence in the system's predictive analytics for detecting potential future problems within the ICT operations, 32.1% of participants strongly agreed and an additional 50% agreed while only 17.9% were neutral. This indicates a strong consensus among participants regarding the artefact's predictive capabilities in averting potential ICT problems. In summary, the artefact's predictive analytics enhance the ICT department's ability to detect future problems by ensuring efficient and responsive operations, early identification of potential issues, successful prediction, and prevention of problems, and instilling confidence in the accuracy of predictive insights. These capabilities collectively empower the ICT department to proactively address challenges and maintain the reliability and efficiency of ICT operations.

Table 6.12 User Scalability

Items	SD	D	N	A	SA
I am satisfied with the system's speed and responsiveness.	0	0	4	14	10
	0,0%	0,0%	14,3%	50,0%	35,7%
System's early detection of potential problems through predictive analytics positively impacted ICT operations.	0	1	4	15	8
	0,0%	3,6%	14,3%	53,6%	28,6%
System successfully predicted and prevented impending ICT issues before they escalated.	0	0	6	13	9
	0,0%	0,0%	21,4%	46,4%	32,1%
I have confidence in the system's predictive analytics for detecting potential future problems within the ICT operations.	0	0	5	14	9
	0,0%	0,0%	17,9%	50,0%	32,1%
I am satisfied with the system's speed and responsiveness.	0	0	4	14	10
	0,0%	0,0%	14,3%	50,0%	35,7%

Note: SD = Strongly Disagree, D = Disagree, N = Neutral, A = Agree, SA = Strongly Agree

6.5 Reliability Analysis

The Cronbach's alpha is the most used indicator of internal consistency. It provides reliability estimates from the consistency of item responses from a single assessment. The generally agreed upon lower limit for Cronbach's alpha is 0.7 (Hair, Anderson, Tatham & Black, 1998). Additionally, George and Mallery (2019) offer a set of guidelines for interpreting reliability coefficients, which serve as valuable benchmarks for assessing the reliability of measurement instruments. According to their recommendations, a reliability coefficient > 0.9 is indicative of an excellent level of reliability, suggesting that the instrument consistently produces consistent results. A coefficient > 0.8 is considered good, signifying a high degree of reliability. The coefficient > 0.7, is deemed acceptable, implying that the instrument provides reasonably reliable measurements. However, if the coefficient is > 0.6, it raises questions about the instrument's reliability, and a coefficient of > 0.5 is considered poor. A coefficient < 0.5 is deemed unacceptable, indicating that the instrument's reliability is highly questionable. These guidelines offer a valuable framework for researchers to gauge the reliability of their measurement tools, ensuring that they produce dependable and consistent results. The reliability values for all five constructs are presented in Table 6.13 below.

Table 6.13 Reliability

Construct	Cronbach's Alpha	Number of Items
Decision Support System	0.717	5
Scalability	0.805	4
User Satisfaction	0.826	7
Integration	0.539	2
Efficiency	0.712	2

The "decision support system" consisted of 5 items (α = .71), the "scalability" consisted of 4 item (α = .80), the "user satisfaction" consisted of 7 items (α = .82), the "integration" consisted of 2 items (α = .53), and the "efficiency" consisted of 2 items (α = .71). These values indicate that the items within these constructs are reasonably consistent with one another, suggesting that the measures are reliable for assessing their respective domains. The assessment of the reliability and internal consistency of the five constructs indicates the Efficiency, Scalability, User Satisfaction and Decision Support constructs exhibit acceptable to strong internal consistency with Cronbach's Alpha values (Hair, Anderson, Tatham & Black, 1998). However, the Integration construct shows relatively poor internal consistency with a Cronbach's Alpha of .53, implying that the items in this construct may benefit from refinement or the addition of new items to enhance their overall consistency and reliability.

6.5.1 Correlation Analysis

The correlation coefficient is a measure used to quantify the level of association or closeness, between dependent variables. This concept was discussed by Hair *et al.* (1998). The connection between two variables is indicated by the sign of the correlation coefficient which can be positive or negative. The correlation coefficient ranges from -1 to 1. A correlation of 0 means there is no relationship between the variables, while a correlation of 1 indicates a relationship and -1 signifies a perfect negative relationship. Numerous authors have proposed interpretations for values between 0 and 1. Cohen (2013, 79-81) proposed the following rules for interpretation; a correlation coefficient in the range of 0.10 to 0.29 is considered weak or small a coefficient ranging from 0.30 to 0.49 is seen as moderate or medium and a coefficient falling within the range of 0.50 to 1.0 is considered strong or large. These guidelines offer a framework for understanding the strength of the relationship between variables based on their correlation coefficient. The analysis was performed using Pearson product moment correlation coefficients to measure relationship between Efficiency, Scalability, User Satisfaction, Integration and Decision Support System.

Table 6.14 Correlation

		Scalability	User Satisfaction	Integration	Efficiency	Decision Support
Scalability	Pearson Correlation	1	.401*	.353	.446*	.556**
	Sig. (2-tailed)		.034	.065	.017	.002
	N		28	28	28	28
User Satisfaction	Pearson Correlation		1	.575**	-.049	.353
	Sig. (2-tailed)			.001	.803	.065
	N			28	28	28
Integration	Pearson Correlation			1	.403*	.504**
	Sig. (2-tailed)				.033	.006
	N				28	28
Efficiency	Pearson Correlation				1	.668**
	Sig. (2-tailed)					<.001
	N					28
Decision Support	Pearson Correlation					1
	Sig. (2-tailed)					
	N					

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

As shown in Table 6.14 above, there is a statistically significant (p-value < 0.02) strong positive correlation ($r = 0{,}556$) between Scalability and Decision Support, indicating that as Scalability increases, so does the effectiveness of the Decision Support. Similarly, these observations indicate a strong positive correlation between Efficiency and the Decision Support ($r = 0.668$, p-value < 0.01), highlighting that higher Efficiency links to a more effective Decision Support. The results indicate a statistically significant relationship (p-value < 0.06) characterised by a strong positive correlation ($r = 0.504$) between Integration and the Decision Support. User Satisfaction and Decision Support is not significant ($p > 0.65$) and $r = 0.353$. The correlation coefficient ($r = 0.353$) suggests that, even though there is a positive correlation, it does not represent a statistically significant correlation. In practical terms, this implies that changes in User Satisfaction do not reliably predict changes in the use or effectiveness of the Decision Support. These findings underscore the interplay among these constructs offering valuable insights for optimising organisational performance and enhancing user satisfaction in the artefact.

6.5.2 Evaluating Multiple Regression

Multiple linear regression analysis is a statistical method used to model the relationship between a dependent variable and multiple independent or predictor variables. It extends the concept of simple linear regression, which deals with one dependent variable and one independent variable, to situations where there are two or more independent variables. In multiple linear regression, the goal is to create a linear equation that predicts the value of the dependent variable based on the values of the independent variables. For this study, multiple regression aimed to assess the ability of two control measures (Scalability, User Satisfaction, Integration and Efficiency) to influence the dependent variable (Decision Support). Preliminary analyses ensured no violation of the assumptions of normality, linearity, multicollinearity and homoscedasticity.

Table 6.15 ANOVA Results

ANOVA[a]					
Model	**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
Regression	4.747	4	1.187	9.030	<,001[b]
Residual	3.023	23	.131		
Total	7.770	27			

Note: [a] Dependent Variable: Decision Support. [b] Predictors: (Constant), Efficiency, User Satisfaction, Scalability, Integration

It is evident from Table 6.15 that multiple regression is significant (p-value < 0.05). This finding suggests that there is a linear relationship between independent variables (Efficiency, User Satisfaction, Scalability, Integration) and dependent variables (Decision Support).

6.5.3 Multiple Linear Relationship Assumption

Prior to interpreting the beta coefficient, it is ideal to check if the multi linear regression model adheres to the multiple linear regression assumptions. For any unmet assumptions, the results of the regression may not be trustworthy. These assumptions are multicollinearity, homoscedasticity, normality and outliers.

Assumption of Multicollinearity

This assumption evaluates if there are connections between the predictor variables. When multicollinearity exists, it can be difficult to determine the impacts of each predictor on the variable. Detecting and dealing with multicollinearity is important to maintain the stability of the model. Correlation analysis, tolerance values and the variance inflation factor measure multicollinearity. According to Pallant (2020), Correlations that are 0.8 or 0.9 should be a cause for concern. If you come across any of these the researcher may need to consider removing one variable from any pair of correlated variables. Based on the correlations presented in Table 5.14, none of the variables exhibit a correlation coefficient greater than 0.6, suggesting that the model does not suffer from multicollinearity.

Assumption of Homoscedasticity

This assumption suggests that the variability of the residual values should remain consistent regardless of the levels of the predictor variables. In other words, it means that the dispersion of the residual values should be stable. When there is heteroscedasticity the dispersion varies, which can result in estimations of coefficients and standard errors. The scatterplot produced from SPSS assesses the homoscedasticity assumption.

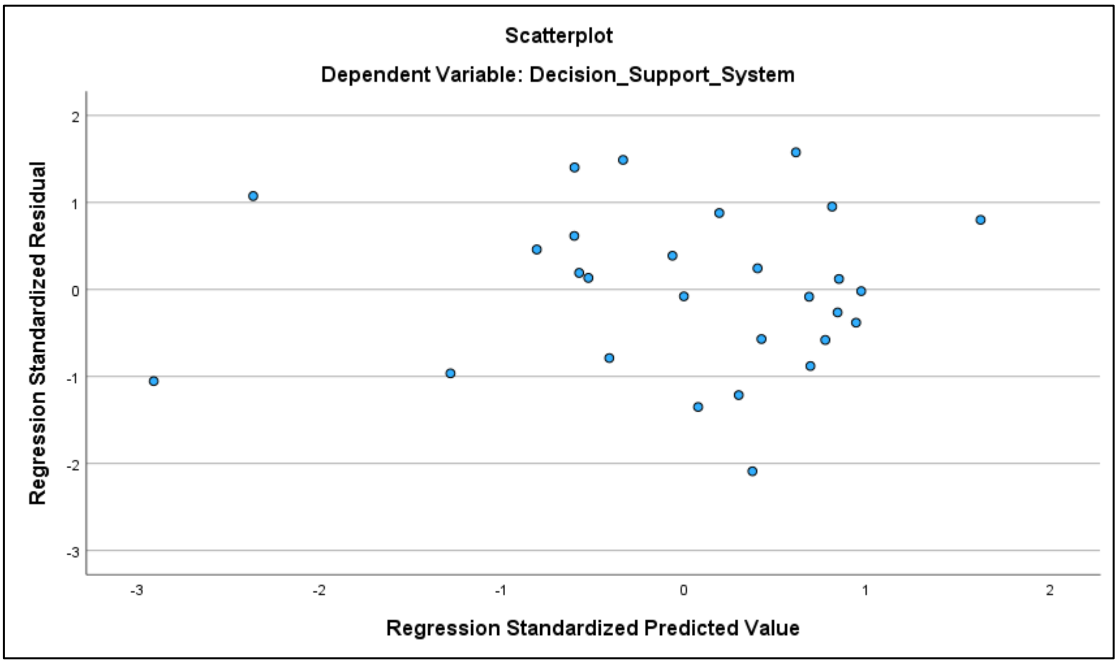


Figure 6.4 Scatterplot

When examining homoscedasticity scatterplots are useful to observe whether the dispersion of the residuals values constant as you progress along the x axis (the variable). If the scatter of data points expands or contracts as you move from left to right, it could suggest the presence of heteroscedasticity. As reflected on Figure 6.4, the scatter of residual values in the study's scatterplot suggests that homoscedasticity is not valid.

Assumption of Normality

Another assumption we make is that the residuals which are the discrepancies between the observed values and the predicted values adhere to a distribution. It is important to note that when deviations occur from this normality it can impact the precision of confidence intervals and hypothesis tests. To evaluate the normality of residuals we often employ tools like histograms and pp plots. In normal pp plots the residual points are lying along the diagonal line from left to right suggesting no major deviations from normality as per Figure 6.5.

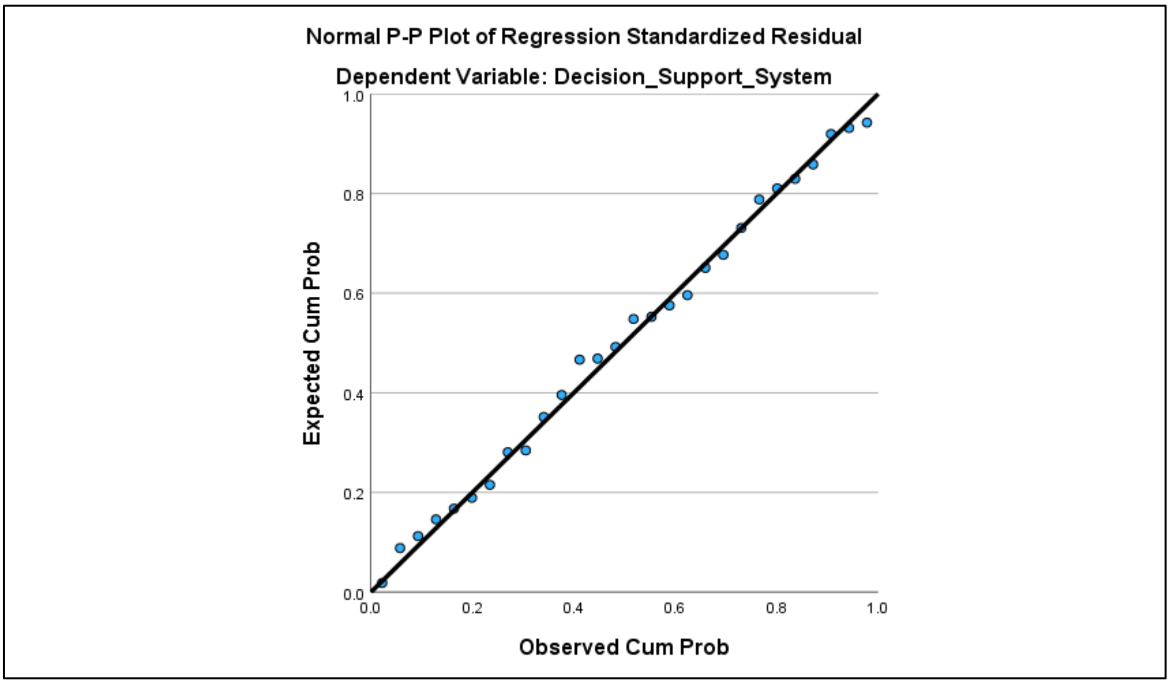


Figure 6.5 Normal pp plot

Assumption of Outliers

Outliers refer to data points that deviate significantly from the pattern of the data. These exceptional data points have the potential to exert influence on the regression model. It is crucial to detect and address these outliers to prevent them from distorting the results of regression analysis. In this study the outliner was determined by comparing the calculated maximum Mahalanobis distance value against Mahalanobis critical value. For there not to be outliers the maximum Mahalanobis distance value must be less than Mahalanobis critical value.

As depicted in Table 6.16 below, Mahalanobis critical value is determined by the number of independent variables in the model (Pallant, 2020).

Table 6.16 Mahalanobis Critical Value (Pallant, 2020)

Number of dependent variables	Critical value	Number of dependent variables	Critical value	Number of dependent variables	Critical value
2	13.82	5	20.52	8	26.13
3	16.27	6	22.46	9	27.88

4	18.47	7	24.32	10	29.59

The maximum Mahalanobis distance value for this study was 10.47 for independent variables (Efficiency, User Satisfaction, Scalability, Integration).

Table 6.17 Residual Statistics

Values[a]	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	2.6679	4.5672	3.8878	.41930	28
Std. Predicted Value	-2.909	1.620	.000	1.000	28
Standard Error of Predicted Value	.095	.233	.149	.038	28
Adjusted Predicted Value	2.7623	4.5137	3.9031	.42105	28
Residual	-.75742	.57122	.00000	.33459	28
Std. Residual	-2.089	1.576	.000	.923	28
Stud. Residual	-2.361	1.652	-.019	1.019	28
Deleted Residual	-.96692	.62767	-.01531	.41061	28
Stud. Deleted Residual	-2.652	1.721	-.026	1.059	28
Mahalanobis Distance	.886	10.169	3.857	2.538	28
Cook's Distance	.000	.308	.047	.072	28
Centred Leverage Value	.033	.377	.143	.094	28

Note. [a] Dependent Variable: Decision Support

As per Table 6.17, the study's calculated critical maximum value is 10.169, meaning it is less than 18.47. There are no outliers such that all the multiple linear regression has been adhered to, enabling the evaluation of multiple linear regression analysis.

6.5.4 Evaluation of Independent Variable

Table 6.18 Coefficients

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	.153	.689		.222	.826
Scalability	.146	.155	.156	.938	.358
User Satisfaction	.307	.197	.300	1.560	.132
Integration	.036	.195	.035	.184	.856
Efficiency	.468	.139	.599	3.375	.003

It is evident from Table 6.18 that Efficient (p-value = 0.003) is the only statistically significant predictor of the dependent variable (Decision Support) in this model. This finding suggests that "Efficient" is a critical factor that significantly affects the "Decision Support". The use of the coefficient of determination (R^2 value) is an accepted approach in regression analysis to validate a model. The R^2 value represents the amount of variance in the variable (Decision Support), attributed to the independent variable(s) used in the model. A higher R^2 value, closer to one, indicates that a sizable portion of the variance in the variable results from the independent variable(s) suggesting a fit. On the other hand a lower R^2 value, closer to zero suggests that there is no explanation for the variance in the dependent variable based on the independent variable(s) indicating a weaker relationship. The coefficient of determination (R^2 value) validates the study's model.

Table 6.19 Model[b] Summary

R	R Square	Adjusted R Square	Std. Error of the Estimate
.782[a]	.611	.543	.36252

Note. [a] Predictors: (Constant), Efficiency, User Satisfaction, Scalability, Integration. [b] Dependent Variable: Decision Support

Table 6.19 shows the R^2 value of 0.611 for the model suggesting that the independent variable Efficiency explains 61.1% of the variance in the dependent variable (Decision Support). In other words, Efficiency has a substantial influence on explaining the variations observed in the Decision Support System. This statistic provides valuable insight into how well the

Efficiency variable predicts or accounts for the changes in the Decision Support System variable.

6.6 AIDSS Artefact Practical implications

Business Process Automation

As seen on Figure 6.6 below, with AIDSS request for automation AI can be deployed to receive and process requests from users thereby enhance decision making. The proposed artefact can understand natural language, making it easier and more intuitive for users to submit their requests.

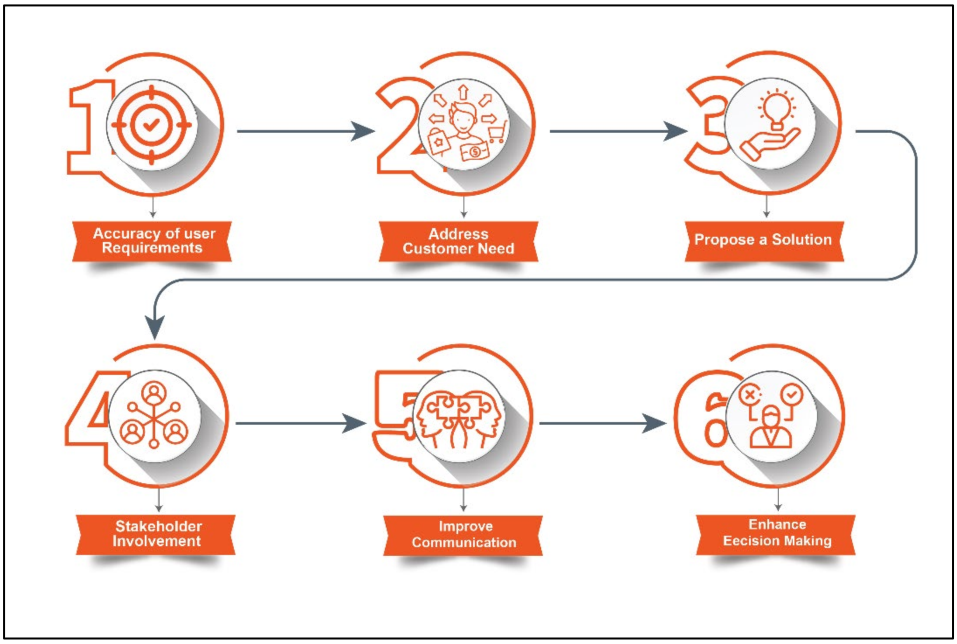


Figure 6.6 Benefits of innovative business process automation

The use of AI in request automation significantly reduces manual intervention and expedites the process. By automating the request handling and decision-making steps, AI systems can process many requests simultaneously, leading to faster response times and increased efficiency. Moreover, AIDSS can learn from user interactions and feedback, continually improving its performance and accuracy over time.

__Preventative IT Asset Management__

As depicted in Figure 6.7 below, the case university can benefit from the prototype AIDSS to enhance efficiency, reduce response times, and improve overall incident management which will positively impact decision-making in the ICT department.

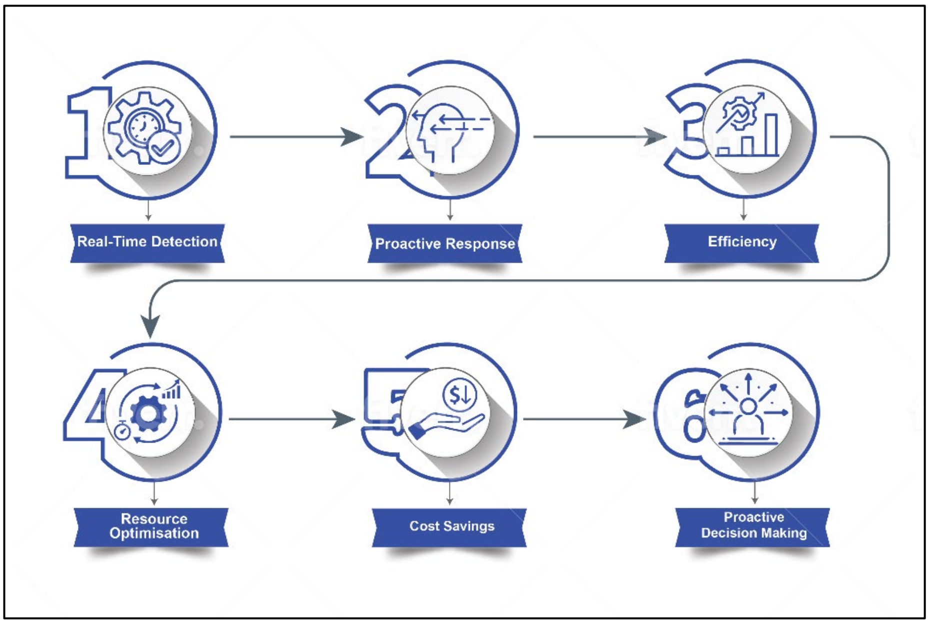


Figure 6.7 Benefits of innovative preventative maintenance

The AI-enabled ecosystem offers the promise of optimising resource utilisation. This optimisation aligns seamlessly with the university's goal of resource maximisation, resulting in enhanced institutional effectiveness in decision making.

Predictive Network Monitoring

AI can significantly improve network management in the ICT department by introducing automation and intelligence into the process as depicted on Figure 6.8 below. The AIDSS can continuously monitor network traffic and device performance, identifying patterns and anomalies that might be difficult to detect through manual methods.

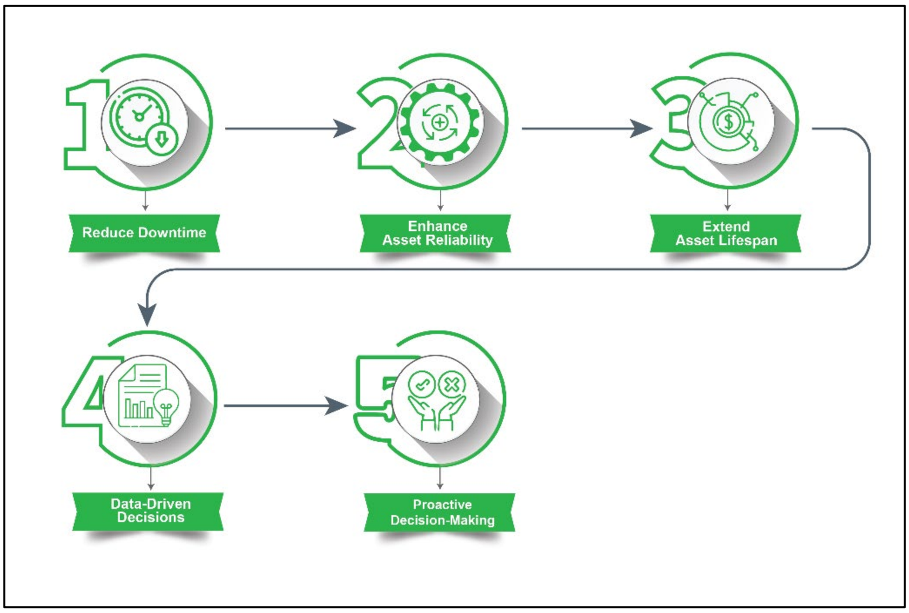


Figure 6.8 Benefits of innovative prediction

AI algorithms can analyse massive amounts of data quickly, allowing for more proactive and timely responses to network events. AI can also simplify network management tasks through natural language processing and conversational interfaces. AIDSS can assist network administrators and end-users by providing instant support, answering queries, and offering guidance on network-related issues, streamlining the support process, thereby improving decision making.

With sufficient funding, it is possible to enhance the User Interface (UI) of the AI decision support system. Adequate budget allocation would enable the incorporation of advanced design elements, improved usability features, and the integration of user feedback to create a more intuitive and user-friendly interface. The UI enhancements would contribute to a smoother and more efficient user experience, encouraging greater adoption of the decision support system and maximising its potential to support effective decision-making processes.

Having considered all the valuable feedback received from the evaluation, the researcher made efforts to refine the AI-enabled decision support prototype despite working within limited personal budget constraints. With optimisation in mind, the refinements focused on addressing the most critical aspects highlighted by the reviewer to ensure the prototype's effectiveness. Essential features were enhanced, improving user interface elements, and streamlining data processing capabilities. By making targeted adjustments, the prototype can achieve a more polished and user-friendly experience, aligning it better with the research objectives and ICT department needs. The result will be a more robust and efficient prototype, ready to support and empower decision-makers with data-driven insights, even within the constraints of a limited budget. The integration of AI within decision-support systems holds the potential to convert complexity into clarity, marking significant and profound implications.

6.7 Findings

This study investigated the efficacy of AI as a decision support mechanism, aiming to enhance decision-making processes in universities using the ICT department as a case. The study's outcomes and proposed artefact are specifically geared towards improving decision-making practices within the university context. The primary objective of this study was to develop an AI tool for decision-support within higher education institutions. The selected university served as a case organisation to investigate and understand the effects of AI on decision-making processes. In this chapter the AIDSS artefact's evaluation provided conclusive evidence that the implementation of AI played a crucial role in supporting organisational decision-making to a significant extent. These findings are consistent with the literature survey findings discussed in Chapter Two. The findings indicate that by automating repetitive tasks and streamlining workflows, AI can improve operational efficiency, reduce the need for manual labour and thus enhance decision-making. Moreover, AI-enabled decision support systems can facilitate data-driven decision-making processes that can lead to more effective and economical operations. As a result, the integration of AI technologies in the ICT department can have a positive impact on the university's financial bottom line and enhance overall productivity and performance. The ICT department management faces the challenge of enhancing the AI skills of its employees to enable them to effectively embrace AI technology. By doing so, employees can fully leverage the potential benefits of AI and increase their productivity in the workplace. Improving AI skills will empower the workforce to adapt to AI tools comfortably, leading to more efficient and effective use of technology to achieve organisational goals. Finally, the AI-enabled decision support prototype should have the flexibility to adapt to new types of devices and technologies that are added to the network over time.

As stated in Chapter One, AI decision support systems can play a crucial role in facilitating effective decision-making within organisations. Given the artefact's significance, it becomes imperative for institutions of higher education, especially universities to develop suitable policy frameworks that promote the acceptance and utilisation of AI. These policy frameworks should aim to create a conducive environment for the integration of AI technologies into various aspects of university operations, including decision-making processes. By doing so, universities can harness the full potential of AI to enhance efficiency, productivity, and overall performance while ensuring that its implementation aligns with ethical considerations and best practices. Both the research findings and the existing literature have consistently highlighted a strong relationship between AI and decision-making, supporting the premise stated in the problem statement. However, the research findings also indicate that despite this strong relationship, there is currently a lack of effective coordination between AI and decision-making functions. This suggests that while the potential for AI to enhance decision-making exists, there are challenges in effectively integrating AI technologies into the decision-making processes. Further practical exploration to improve the coordination of AI and decision-making functions are necessary to fully realise the benefits of AI in this context.

6.8 Chapter Summary

The prototype of the AIDSS was developed in the previous chapter. In this chapter it was presented to ICT personnel for feedback and validation. The success of the artefact was measured against established evaluation criteria, ensuring alignment with the decision-making landscape within the ICT department. Every participant evaluated the prototype using a questionnaire based on metrics which was a component of the Goal Question Metric approach, a method for measuring software metrics. This approach enhanced the relevance, usability, and overall impact of the AIDSS, leading to improved decision-making processes and outcomes specifically catered to the ICT domain's needs and objectives. The GQM evaluation approach allowed the researcher to systematically gather data and feedback from users, experts, and stakeholders involved in the evaluation process. This feedback played a crucial role in understanding the system's strengths and weaknesses, user satisfaction, and the extent to which the prototype met the desired objectives. The findings from the evaluation using GQM provided valuable information for refining the AIDSS prototype. The researcher identified areas where the system performed well and areas that needed improvement. This iterative process of evaluation and refinement is essential in developing a robust and effective decision support system. Moreover, the insights gained from the evaluation contributed to the broader field of artificial intelligence research, guiding the development of similar decision support systems in various domains. In conclusion, the application of the Goal Question Metric approach in evaluating the AIDSS prototype was a well-structured and insightful process. It allowed the researcher to set clear goals, ask relevant questions, and utilise appropriate metrics to assess the system's performance effectively. The outcome of this evaluation played a vital role in enhancing the AIDSS prototype, ensuring it meets the operational needs and expectations of the users, and ultimately contributing to the advancement of decision support systems powered by artificial intelligence. It is evident from the artefact that AIDSS offers benefits to the ICT team aiming to enhance decision making and optimise IT operations. By utilising intelligence methods to analyse intricate and ever-changing data, AIDSS aids in identifying patterns, detecting anomalies and forecasting future trends. This empowers the ICT team to make effective decisions resulting in improved efficiency.

In the subsequent chapter, the study concluded with a comprehensive review of the research questions and objectives. Moreover, it addresses the identification of limitations, contributions and recommendations derived from the research findings. Additionally, the chapter explores potential for future research that could further expand and enhance the understanding of artificial intelligence-enabled decision support systems for higher education systems.

CHAPTER 7: CONCLUSION

7.1 Introduction

The previous chapter presented the research findings and recommendations of the study, simultaneously evaluating the artificial intelligence-enabled decision support prototype for higher education institutions. A DSR methodology was used to develop the AIDSS artefact through primary data obtained from the semi structured interviews and observations. The secondary data which contributed towards the development was obtained from the relevant literature review. The AIDSS artefact was refined through user feedback from questionnaires as part of the DSR evaluation process. Three problematic elements supported the development of the prototype:

Business Process Automation: Users typically submit requests through manual channels, such as filling out forms or sending emails, to initiate the automation of specific tasks or processes. After back-and-forth communication and clarification, these requests are then reviewed and processed by the Business Process Architecture who determines the feasibility and priority of each automation request. Once approved, the automation process is implemented by the ICT team or relevant personnel. As we can deduct from this process it is time consuming and negatively affects decision making.

Preventative IT Asset Maintenance: ICT staff typically follow predefined maintenance schedules for assets, conducting periodic inspections, updates, and replacements based on time-based or usage-based thresholds. This approach often relies on human experience and judgment to determine when preventive actions are necessary, and it may lead to either under-maintenance, resulting in asset failures, or over-maintenance, leading to unnecessary costs. The lack of maintenance for IT assets is a flaw that negatively affects the decision-making process and burdens incident management at the case university.

Predictive Network Monitoring: This section in the ICT department at the selected case university involves manually monitoring and configuring the network infrastructure to ensure its smooth operation. Network administrators are responsible for tasks such as device configuration, monitoring network traffic, troubleshooting issues, and ensuring security protocols are in place. It has become apparent that the limited resources available for network monitoring contribute to the department's challenges in making decisions within a timeframe.

This chapter offers a conclusion to the research study. It starts by discussing the contribution made by this study. Next, the research study's objectives, theoretical framework, and research methodology are presented in detail. Subsequently, the limitations of the study and potential opportunities for future research are elaborated upon.

7.2 Revisiting Research Questions and Objectives

In Chapter One, the reader is introduced to the significance of AI and its pivotal role in decision-making processes within organisations. The chapter lays the foundation for understanding the growing importance of AI in modern organisational environments, where data-driven and informed decision-making have become imperative for success. Through insightful discussions and relevant examples, chapters one and two highlights how AI technologies can revolutionise and enhance decision-making practices, providing organisations with a competitive edge. The potential benefits of AI in automating routine tasks, analysing vast datasets, and offering predictive insights are elucidated, demonstrating its transformative impact on organisational efficiency and effectiveness. Moreover, the chapter emphasises the need for organisations to embrace AI technologies as a strategic asset to capitalise on the wealth of information available in today's data-driven world. By setting the stage for the ensuing chapters, the reader gains a comprehensive understanding of why AI and decision-making are inseparable elements for organisational success in the contemporary landscape.

The primary issue addressed in this study revolves around the challenges faced by both management and employees in making well-informed decisions in the ICT department. The existing decision-making processes suffer from fragmentation, primarily stemming from disparities in systems and the presence of vast volumes of data. Therefore, decision-makers encounter difficulties in accessing, integrating, and processing information effectively. The lack of a cohesive decision-making framework hinders the case university's ability to harness the full potential of available data, leading to suboptimal choices and missed opportunities. The complexity of handling extensive data further exacerbates the problem, as traditional approaches prove insufficient in providing timely and accurate insights. Therefore, the study aims to rectify these issues by developing a unified and AI-enabled decision support system, which can streamline decision-making processes, promote data integration, and empower ICT department employees to make more informed and tactical choices.

Section 7.2 conveniently revisits the research questions and objectives established in Chapter One, set out as Table 1.1 and listed below as Table 7.1.

Table 7.1 Revisiting Research Questions and Research Objectives

Research Questions	Research Objectives
MRQ: How can an AI-enabled decision support system be developed for decision-making within the ICT department at the university?	
SRQ1: What are the various decision-making elements that affect decision-making within the ICT department at the university?	**RO1:** To determine how various decision-making elements affect decision-making within the ICT department at the university.
SRQ2: How is operational decision-making performed within the ICT department at the university?	**RO2:** To determine how operational decision-making occurs within the ICT department at the university.
SRQ3: What challenges are decision-makers facing when making operational decisions within the ICT department at the university?	**RO3:** To assess challenges faced by decision-makers when making operational decisions within the ICT department at the university.
SRQ4: How can an AI-enabled decision support system be developed for decision-making within the ICT department at the university?	**RO4:** To develop an AI-enabled decision support system to support operational decision-making within the ICT department at the university.

The answering of the secondary research questions (SRQ1 – SRQ4) collectively addresses the main research question (MRQ). The provision of answers to these questions simultaneously meets the associated objectives of the study (RO1 – RO4).

SRQ1: What are the various decision-making elements that affect decision-making within the ICT department at the university?

An extensive evaluation of the existing literature was undertaken to gain a comprehensive understanding of the relevant concepts, theories, and best practices in the domain of decision support systems and artificial intelligence (Chapter Two). This literature review served as a vital foundation for informing the design and development of the AI-enabled DSS. Additionally, to gain deeper insights into the specific challenges faced by the ICT department and the decision-making processes, the researcher conducted semi-structured interviews with decision-makers (Chapter Four). These interviews provided valuable first-hand perspectives from employees and management involved in decision-making within the department. The information gleaned from these interviews proved instrumental in identifying the pain points, inefficiencies, and potential areas of improvement within the existing decision-making system. Furthermore, direct observations were made to better understand the operational aspects and dynamics of the ICT department's decision-making processes (Chapter Four). By observing the decision-makers in action, the researcher could identify the decision-making elements' practical implementation and assess the artefact's strengths and weaknesses in real-world scenarios.

The integration of these three methods - literature review, semi-structured interviews, and direct observations facilitated a comprehensive and holistic approach to explore the problem and identify the essential elements required for developing an effective AI-enabled DSS. This multi-dimensional research strategy ensured that the resulting AI-enabled DSS would be tailored to address the specific needs and challenges of the ICT department at the university, ultimately enhancing decision-making processes and enabling more informed, data-driven choices.

SRQ2: How is operational decision-making performed within the ICT department at the university?

This method involved a thorough examination of the key components that contribute to decision-making practices in the department, aiming to identify strengths, weaknesses, and potential areas for improvement (Chapter Four). By analysing these elements, the researcher sought to gain insights into the current decision-making process and lay the groundwork for the development of an effective AIDSS tailored to the department's needs. Some of the observed elements:

Data Integration and Centralisation: The AIDSS facilitated seamless integration and centralisation of data from various sources within the ICT department. This centralised repository enables decision-makers to access a unified and comprehensive dataset, enhancing university data-driven decisions.

Observation in Real Time: The AIDSS provided real-time monitoring of key performance indicators. This feature can empower decision-makers in the ICT department to stay updated on critical metrics and respond promptly to changing circumstances.

Machine Learning Algorithms: Implementing machine learning algorithms within the AIDSS enabled it to continuously learn from new data and improve its decision-making recommendations over time. This self-learning capability enhances the artefact's accuracy and adaptability.

Visualisation and Decision Support Tools: The AIDSS employs advanced data visualisation techniques and decision support tools to present complex information in a user-friendly manner. Visualisations aid comprehension and facilitate more effective decision-making processes.

SRQ3: What challenges are decision-makers facing when making operational decisions within the ICT department at the university?

The challenges faced by decision-makers within the ICT department while making operational decisions at the university was effectively accomplished through a multi-step approach. Firstly, the researcher utilised a comprehensive DSR methodology that incorporated interviews and observations as data collection techniques (Chapters Four). By using this approach, the researcher gained valuable insights from diverse perspectives, allowing for a thorough understanding of the decision-making challenges in the ICT department. Next, the AIDSS Artefact was developed based on the data results and the identified challenges. The design and demonstration of the AIDSS Artefact allowed decision-makers and other stakeholders to witness how the system could potentially alleviate the identified challenges and enhance operational decision-making processes. Through simulated scenarios and practical demonstrations, decision-makers could gauge the potential impact of the AIDSS on their decision-making practices. The development of the AIDSS Artefact was carried out with careful attention to tailor it specifically to the unique needs and requirements of the case university’s ICT department. The artefact was equipped with advanced features, including data integration, predictive analytics, real-time monitoring, and user-friendly dashboard to address the challenges faced by decision-makers effectively.

Finally, the comprehensive approach involving the design, demonstration and development of the AIDSS Artefact provided valuable insights into the challenges surrounding operational decision-making within the ICT department. Additionally, it demonstrated the potential of the AIDSS to serve as an efficient and powerful tool to aid decision-makers in making more informed and strategic choices within the university's ICT operations. The results obtained from this research can provide a basis for further research and implementations seeking to enhance decision-making processes in similar organisational settings.

SRQ4: How can an AI-enabled decision support system be developed for decision-making within the ICT department at the university?

The researcher followed a rigorous and systematic approach. Firstly, the AIDSS was methodically designed and developed, incorporating advanced AI algorithms and decision support features tailored to the specific needs of the ICT department (Chapter Five). Following the development phase, the researcher proceeded to test and evaluate the AIDSS artefact using a quantitative Goal Question Metric questionnaire, detailed in Chapter Five. This questionnaire was carefully crafted to measure the artefact's performance, effectiveness, and user satisfaction. Decision-makers and stakeholders within the ICT department were invited to participate in the evaluation process. The GQM questionnaire encompassed various key performance indicators, such as the artefact's response time, accuracy of predictive analytics, user interface intuitiveness, and overall user experience. Participants were asked to provide their feedback and ratings based on predefined Likert scale.

The data collected from the questionnaire responses was analysed, and SPSS was employed to draw meaningful conclusions about the AIDSS artefact's strengths and areas for improvement. The researcher used the feedback to identify any potential shortcomings and to refine the artefact based on the user's preferences and needs. Through this quantitative evaluation process, the researcher gained valuable insights into the AIDSS artefact's performance and its potential impact on operational decision-making within the ICT department. The results provided empirical evidence of the artefact's effectiveness and aided in validating the successful achievement of the research objective.

MRQ: How can an AI-enabled decision support system be developed for decision-making within the ICT department at the university?

The preceding secondary research questions (SRQ1-SRQ4) severally contributed to the answering of the main research question (MRQ) as follows:

- SRQ1 – identified various decision-making elements.
- SRQ2 – explored operational decision-making.
- SRQ3 – reviewed challenges faced by operational decision-makers.
- SRQ4 – considered developmental factors for an AI-enabled decision support system.

7.3 Theoretical Framework

In Chapter Four of the research, the development cycle of the AIDSS artefact was guided by the Information Systems Architectural (ISA) Design Theory, which served as a foundational theoretical framework. This choice of theory was driven by the desire to establish a comprehensive understanding of how AI, Intelligent Decision Support Systems, and the Fourth Industrial Revolution technological advancements could synergise and benefit decision-making processes. By adopting the ISA Design Theory, the research aimed to bridge the gap between theoretical concepts and practical implementation, thereby creating a practical and efficient artificial intelligence-enabled decision support system. The theory provided a structured and systematic approach to designing the AIDSS, ensuring that it is well-aligned with the current technological landscape and the emerging trends of the Fourth Industrial Revolution. The application of ISA aimed to capitalise on the potential of AI and DSS technologies to streamline decision-making processes. By incorporating advanced predictive and analytical capabilities, the AIDSS aspired to reduce the time required to make informed judgments significantly. The system's ability to process and analyse vast amounts of data swiftly would empower decision-makers with real-time and accurate information, enabling them to respond promptly to dynamic situations. Moreover, the ISA-based design was envisioned to enhance the consistency and quality of decisions made within the selected university. By adhering to a standardised and well-defined architectural approach, the AIDSS sought to minimise biases and ensure that decisions are based on objective and data-driven insights.

As alluded in Chapter Three, the descriptive decision theory served as a lens to understand how decisions are made in the ICT department of the case university. Combining the practical principles of descriptive decision theory with the potency of artificial intelligence-enabled decision support systems introduced a formidable approach to informed decision-making. In the context of the study this allowed the system to analyse datasets uncover hidden trends and provide insights that may have otherwise gone unnoticed. This approach was particularly useful in the IT Asset Preventative Maintenance process. By combining data and analytics the system could identify usage patterns, performance trends and potential vulnerabilities in IT assets. Accordingly, the descriptive decision theory shed line in the consideration of automated systems and technologies to streamline and optimise the process of handling and fulfilling requests for Business Process Automation. The same concept also applied to network monitoring where predictive analytics played a role, in anticipating network glitches and downtimes. Taking an approach historical data and sophisticated algorithms were used to predict disruptions. This allowed IT teams to take measures and ensure operations. The combination of human cantered insights and advanced analysis not only improved decision, but also transformed IT management and network stability. It provided a path forward in our technological landscape with more confidence.

7.4 Methodology and Evaluation

This study was conducted within a Pragmatism paradigm under the DSR methodology. The paradigm allowed for use of a mixed-method approach that involved multiple data collection techniques to inform the designing of an artefact. The methodological contribution of this study is grounded in the adoption of Design Science Research (DSR) as the overarching approach to create a novel artefact aimed at addressing a decision-making problem within a public-funded university. DSR, as a research paradigm, focuses on the systematic design, development, and evaluation of innovative solutions to real-world problems. By applying DSR, this study pursued a goal-oriented and problem-solving approach to design an artefact that specifically targets the decision-making challenges faced by the university's ICT department. Through the DSR framework, the research seamlessly integrated theory and practice, leveraging existing knowledge and insights to inform the design process. The study not only sought to gain a comprehensive understanding of the decision-making context within the university's ICT department but also actively engaged with decision-makers to co-create the artefact that would meet their unique needs.

After considering the various options for approaching Design Science research, this study chose to adopt Kuechler and Vaishnavi (2008) conceptual framework, adopting the following guidelines:

Problem Awareness: At the case university, the poor decision-making is a direct outcome of the information systems functioning in isolated silos and generating substantial volumes of complex data that are challenging to process using traditional approaches.

Suggestion: As detailed in Chapter Four, the aim of the proposed system is to improve decision-making, alleviate ICT support personnel from monotonous tasks, reduce downtime of operational services, and ultimately enhance customer satisfaction while achieving cost-saving measures.

Development: As per chapter Five, this study developed an artefact for artificial intelligence-enabled decision support system for higher education institutions.

Evaluation: As detailed in Chapter Six, the artefact was evaluated using a Goal Question Metric questionnaire completed by the users.

Conclusion: The study successfully achieved its aim, and Chapter Seven provides a detailed account of the contributions made by this research. A research paper was published as a contribution to the study.

The use of DSR in this study was particularly beneficial in fostering an iterative development process, where the initial prototype was continuously refined based on feedback and evaluations from ICT personnel. This iterative nature allowed the researcher to adapt and tailor the artefact to the specific requirements of the case university, ultimately enhancing its practical relevance and effectiveness. By employing DSR, this research contributes to the field of decision support systems in educational settings, showcasing the value of a human-centred and problem-driven approach in creating innovative solutions. The resulting artefact, tailored to the public-funded university's decision-making context, holds the potential to significantly improve decision-making processes, optimise resource allocation, and ultimately enhance the overall efficiency and effectiveness of the university's ICT operations. The methodological framework of DSR applied in this study serves as a model for future research endeavours that seek to bridge the gap between academia and real-world practice, with a focus on delivering impactful and tangible solutions to decision-making challenges in various domains. The proposed solution can help improve the decision-making process in the ICT department. In this research study, data validity and reliability were crucially considered, and the following measures were implemented to ensure their integrity.

7.4.1 Data Triangulation

Data was collected using qualitative and quantitative methods resulting in the design, development and evaluation of a new AI-enabled decision support system for decision-making in the ICT department. Semi-structured interviews were used for qualitative data which contributed into the development of the artefact. The interview results were analysed using thematic analysis. In contrast, the questionnaire was utilised for quantitative data to assess the user acceptance of the artefact. The quantitative results were analysed and interpreted using SPSS software. The secondary data which contributed towards the development was obtained from the relevant literature analysis. Figure 7.1 shows the data triangulation process that was followed for the study. Cox and Hassard (2005) argue that triangulation of data is a research process that encompasses the utilisation of numerous data sources, data collection methods or data analysis techniques to corroborate findings and enhance the overall validity and reliability of research results. Through the integration of many data sources, the researcher achieved a more full and holistic comprehension of the research subject matter, thereby mitigating the potential biases associated with sole reliance on a singular data source or methodology. Therefore, additionally a case study observation was employed to validate the needs of the ICT department and evaluate the decision-making processes of users within an authentic setting. This provided the researcher with insights into operational procedures and the underlying causes of decision-making challenges in the ICT department.

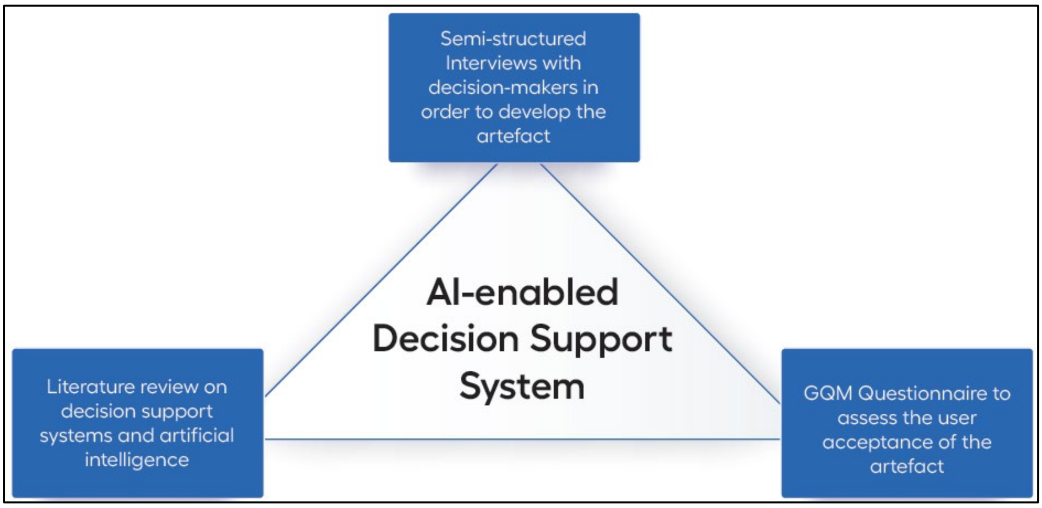


Figure 7.1 Data triangulation

The study focused on developing an AIDSS for the ICT department, data triangulation was employed to collect information and insights from decision-makers within the department. Interviews, questionnaires, observations, and literature analysis were the four data collection methods utilised in this study. Each method provided distinct advantages and complemented one another, leading to a more robust and nuanced understanding of decision-making processes and the specific requirements of the AIDSS. The four areas of data collection using Hevner *et al.* (2008) DSR framework are:

Data Collection Area 1: The process of building and evaluating the AIDSS artefact involved establishing requirements from the ICT department as the problem domain. This critical step entailed thoroughly analysing the ICT department to identify the challenges and objectives faced by decision-makers within this specific context. Objectives were defined based on the problem analysis, and functional and non-functional requirements were specified to address the unique decision-making needs of the ICT department. Domain experts within the ICT department were actively involved to evaluate artefact user requirements and preferences, ensuring that the AIDSS was tailored to their real-world challenges.

Data Collection Area 2*:* During the process of building the artefact, available knowledge contributions were taken into consideration to aid in its development. Interviews were conducted to extract information from decision-makers within the ICT department. These interviews served as a valuable means of gathering insights and expertise from key stakeholders, allowing for a more comprehensive understanding of the specific requirements and challenges within the ICT domain. The data acquired from these interviews had a pivotal role in influencing the design and functionalities of the artefact, ensuring that it was aligned with the real-world needs and objectives of the ICT department. By incorporating the perspectives and knowledge of decision-makers, the resulting artefact was tailored to provide effective decision support and address the practical considerations within the ICT environment.

Data Collection Area 3: To aid in building the artefact, careful consideration was given to the existing environmental practices in the ICT department. Observations were conducted to gain insights into the current practices and processes within the environment. These observations allowed the researcher to assess the strengths and weaknesses of the existing decision-making methods in the context of the artefact's development. By closely observing how decisions were made and executed, the researcher could identify areas for improvement and areas where the proposed artefact could provide value and support. The data collected from these observations helped inform the design and development of the artefact, ensuring that it was well-suited to the specific environmental context. By aligning the artefact with existing practices and processes, its implementation was made more seamless, and decision-makers were more likely to embrace and utilise the new tool effectively. Furthermore, these observations allowed the researcher to identify potential challenges and barriers to successful implementation, enabling them to address these issues proactively during the development phase. Overall, the inclusion of observations as a research method contributed to the artefact's practicality and relevance in the real-world environmental setting. By considering the existing practices, the researcher could build an artefact that not only addressed specific needs but also integrated smoothly into the established decision-making ecosystem, thereby maximising its potential impact and adoption.

Data Collection Area 4: To rigorously demonstrate the utility, efficacy, and quality of the artefact, it was essential to conduct an evaluation, preferably within the organisational environment where it would be deployed. For this purpose, a questionnaire was used as one of the evaluation methods. The questionnaire served as a valuable tool to gather feedback from users who interacted with the artefact in the organisational setting. It provided a structured and standardised way to collect quantitative data on various aspects of the artefact's performance, usability, and effectiveness. Through the questionnaire, users in the ICT department could express their opinions on the artefact's utility in supporting decision-making processes. They could provide insights into how the artefact improved the efficiency and accuracy of decision-making tasks and whether it addressed their specific needs effectively. Moreover, the questionnaire helped measure the artefact's efficacy in meeting its intended objectives. By posing questions related to decision outcomes and performance improvements, the researcher could assess how well the artefact contributed to better decision-making and achieved the defined goals. Furthermore, the questionnaire played a role in evaluating the artefact's quality. Users could rate the system's reliability, usability, and overall satisfaction, providing valuable indicators of its robustness and user-friendliness. By conducting the evaluation in the ICT department, the researcher could ensure that the results accurately reflected the artefact's real-world performance. The feedback collected from the questionnaire offered actionable insights for improvements and refinements, which could be incorporated into subsequent iterations of the artefact.

7.4.2 Evaluation of the Study

This study adopted Morgan’s intersubjective approach (2007), combining both objectivism and subjectivism methodologies to develop an AI-enabled decision support artefact. The integration of these two perspectives allowed for a comprehensive and well-rounded exploration of the research problem stipulated in Chapter One. The objective approach played a pivotal role in the design and evaluation of the decision support artefact. During the design phase, established principles and best practices were employed to ensure the artefact's functionality, efficiency, and overall performance. Additionally, quantitative evaluation methods applied through GQM objectively measured the artefact's effectiveness and validated its capabilities. This data-driven analysis provided concrete evidence of the artefact's success and served as a crucial foundation for its development. On the other hand, the subjective approach was instrumental in gaining a deeper understanding of user needs and preferences. By conducting interviews and observations, the researcher was able to collect qualitative data directly from the users. This user-centric perspective provided invaluable insights into the specific requirements, challenges, and expectations of the target audience. Such considered insights apparent during the development process, ensured the tailoring of the artefact to meet the users' unique needs and enhance their decision-making experiences. The combination of objective and subjective methodologies enriched the research process, enabling a more holistic and balanced understanding of the AI-enabled decision support artefact. By merging the strengths of both approaches, the study created an advanced, user-friendly, and effective tool that holds great promise for supporting decision-makers in real-world scenarios. The intersubjective approach ensures that the artefact is not only efficient and data-driven but also deeply empathetic to the needs and aspirations of its users in the ICT department of the case university. The application of the intersubjective approach established the credibility of the research project.

7.4.3 Evaluation of the Design

In evaluating the design process, the researcher utilised the design evaluation techniques recommended by Hevner *et al.* (2008) for conducting Design Science Research. This section explores the three chosen evaluation approaches, as outlined by Hevner *et al.* (2008). The approaches include:

Observational: It was crucial for the researcher and ICT personnel to understand the purpose and intended functionality of the artefact. The researcher needed to ensure the artefact was addressing specific departmental needs and challenges. This involved studying its features and capabilities for accuracy, reliability and impact on decision-making efficiency in the organisational environment.

Simulation: In the simulation, the researcher used artificial dummy datasets closely resembling real-world data to evaluate the artefact's performance. The configured artefact incorporated appropriate parameters and algorithms to process the artificial data and included laptop hardware and network data. Through execution and analysis, the researcher monitored the artefact's behaviour and accuracy. Assessments encompassed artefact's responses to the dummy data and comparisons made against expected outcomes. Based on the results, the researcher addressed limitations, and iterated on the artefact's design to enhance its capabilities. The use of dummy data in the simulation allowed for rigorous testing and validation, ensuring the artefact's readiness and reliability for the ICT department.

Experimental (Usability Testing): Pertains to the level of simplicity with which users can engage with a given artefact, execute tasks, and successfully accomplish their objectives in a manner that is both effective and efficient. It is a critical factor in determining the success and acceptance of a technological solution. In this stage, ICT department personnel interacted with the artefact to perform typical tasks relevant to decision-making. The researcher observed their actions and gathered feedback through questionnaires. This approach helped identify areas where users encounter difficulties, confusion, or inefficiencies.

By employing the above-mentioned evaluation methods, the research project has successfully fulfilled the criteria and standards set by Design Science, confirming its legitimacy as a valid Design Science research project. The application of these evaluation techniques ensured that the project adhered to the principles of Design Science Research, which aims to create innovative artefacts and assess their efficacy in addressing specific problems. By subjecting the artefact to rigorous scrutiny and analysis, the research study demonstrated its commitment to producing practical and valuable solutions.

7.4.4 Transferability

The issue of transferability in research is a complex one, with various approaches and challenges. Rodon (2008) suggests that the transferability of research results depends on the similarity of the research settings and proposes a framework to support this assessment. Transferability in this study fosters broader relevance, enabling organisations with similar IT infrastructures or decision-making processes to leverage the AIDSS prototype effectively. This not only amplifies the impact of this research but also promotes the scalability and applicability of the AIDSS framework across diverse scenarios, contributing to its long-term viability and utility. Furthermore, transferability encourages the establishment of best practices and benchmarks, facilitating comparisons and benchmarking against similar systems in various settings. In essence, emphasising transferability in your AIDSS study extends the reach and applicability of the research findings, creating a foundation for widespread adoption and continuous improvement in decision support systems across diverse higher education landscapes. Transferability has been achieved as the AIDSS can be applied to other higher education institutions settings with similar characteristics.

7.5 Contribution of the Study

This section discusses the major research contributions.

7.5.1 Originality

For a long period of time, people have been occupied with the concept of Artificial Intelligence and its impact on businesses and academic projects. Guetzkow and Lamont (2004) posit that research should present new discoveries that add new knowledge. This results in originality of knowledge or value of the study. The researcher has been exposed to the development of an artefact for the first time and has fully applied techniques and tools to its development.

originality was achieved by using existing software development tools, data collection techniques towards the development of the artefact.

7.5.2 Theoretical contribution

As discussed in Chapter Five, the AIDSS artefact is the primary contribution of this research study. The aim of the artefact is to solve the decision-making problem at the selected university's ICT department. Implementation of the proposed solution was evaluated using DSR iterative process and Goal Question Metric to determine if it meets user expectations. It was established that information systems are functioning in isolated silos and generating substantial volumes of complex data that prove challenging to process through traditional approaches at the case university. This resulted in poor decision-making which led to the misallocation of valuable resources on technologies that do not align with the organisation's vision. The AIDSS artefact was designed and developed considering the distinctive needs of the case university. The prototype was constructed using the three challenging elements noted above which are business process automation, IT asset preventative maintenance and predictive network monitoring through predictive analytics.

7.5.3 Methodological contribution

This research has made a contribution by adopting the Design Science Research methodology as a guiding theory for a problem-solving approach. By using the framework suggested by Kuechler and Vaishnavi (2008) as detailed in Chapter Five, the researcher successfully created an AI based decision support prototype, which expands upon the existing body of Information Systems literature. This study does not only highlight how AI can be applied in DSS but also emphasises its compatibility within the higher education sector thereby enhancing our understanding in this area.

7.5.4 Multidisciplinary approach contribution

The complex nature of the study emanates from a combination of multiple disciplines, different theories (psychology, economics, Information Systems (IS) and sociology) were pooled together to help explain and develop the artefact. In order to generate new knowledge and insights in the IS discipline, IS scholars advocate for a multidisciplinary approach (Heeks & Bailur, 2007). By drawing theories from other disciplines, this thesis contributes to the multidisciplinary approach to IS enquiry, which is in line with the calls by IS researchers to adopt the approach (Walsham, 2012).

7.5.5 Practical contribution

This study presents a practical application of decision-support systems in South African Universities, contributing significantly to scholarly research on the topic within the region. Through thorough data analysis, it offers valuable insights into the effective integration of such systems into university operational processes. The study recognises the unique challenges and opportunities in the South African context, making its findings particularly relevant for decision-making practices in this setting. By bridging theory and practice, the research enhances decision-making within the academic sphere of South Africa, providing a blueprint for other higher education institutions. Overall, this study's contribution lies in its practical application of decision-support systems, impacting the scholarly research landscape and empowering institutions to make informed, data-driven decisions for their academic communities' improvement. Exploring the adaptability and transferability of the AIDSS to other domains beyond the case university can extend the application of this research. The research focused on Business Automation and preventative maintenance of IT Assets, as well as predictive analytics utilising Natural Language Processing and Machine Learning. The study's scope may expand in the future to explore additional AI functionalities and in different units such as faculties and administration departments.

7.6 Recommendation for future research

Future research can focus on expanding and refining the integration of predictive analytics algorithms within the AIDSS. This could involve using machine learning models and advanced statistical techniques to improve the accuracy of generated insights and predictions. Additionally, exploring real-time predictive analytics and the integration of external data sources could enhance the system's ability to identify trends and anticipate external influences on decision-making.

7.7 Limitations of the research

The researcher highlights some limitations that confronted the study. It is possible to encounter limitations when conducting a study of this magnitude. These limitations or shortcomings could be methodological or researcher-related (Saunders et al., 2019). In many instances, the researcher is confronted with influences beyond one’s control. When faced with limitations, the research methodology and conclusions can be affected (Creswell, 2014). In this thesis, the researcher acknowledges the limitations, so that appropriate suggestions are recommended for future research to avoid encountering the same conditions. Creswell (2012) and Chigada (2014) state that limitations can be used to demonstrate the researcher's critical thought, focus on the research problem, review appropriate and relevant literature and the methods for studying the problem. The first limitation was the absence of prior studies on the development of an AI artefact that could improve decision-making at institutions of higher learning in South Africa. Without the theoretical underpinnings, the researcher could not obtain adequate literature to support the arguments advanced in this thesis. Most of the literature was borrowed from other countries.

The second limitation was the sample size and target population of the study. The participants were ICT personnel. This meant that potential participants were alienated from the study. Had a different research methodology other than design science been used, the sample size would have been larger. The researcher did not have adequate knowledge about the development of the artefact; therefore, a lot of consultations took place, thus, prolonged the completion of the study.

7.8 Final conclusion

The research findings hold the potential to yield advantages for diverse stakeholders, encompassing both employees and management within the case university. The utilisation of the Information Systems Architectural Design Theory provided a solid theoretical underpinning for the development of the AIDSS artefact. It facilitated the integration of innovative technologies from the Fourth Industrial Revolution, empowered by AI and IDSS capabilities. Through the systematic implementation of ISA, the proposed AIDSS aimed to optimise decision-making processes, shorten decision-making time, and elevate the overall quality and reliability of decisions made within the case university. In this research project, ensuring data validity and reliability was of utmost importance. To achieve this, the researcher implemented various measures. First, data triangulation was employed, involving the use of multiple data sources and methods to corroborate and cross-validate the findings. This approach has strengthened the credibility of the collected data and facilitated a more holistic comprehension of the research problem in the case institution. Secondly, the study used multiple research approaches to alleviate potential biases, errors, and inconsistencies, thereby enhancing the study's overall accuracy and trustworthiness. Lastly, by assessing the appropriateness and effectiveness of the research design process, the researcher ensured that it aligned with the research questions and objectives. robustness of the study and bolstered confidence in its conclusions. Transferability is achieved in this study, allowing seamless application of the

AIDSS to similar higher education institutions. This enhances relevance, scalability, and the widespread adoption of the AI-enabled Decision Support System.

The proposed AI-enabled Decision Support System, once implemented in the university's ICT department, promises to improve decision making. With the integration of artificial intelligence, the system has the potential to provide prompt responses, ensuring a more efficient workflow. Moreover, the automation and intelligent capabilities of the system may enhance the overall quality of services rendered. ICT personnel will find relief from time-consuming tasks, allowing them to focus on more strategic and value-adding responsibilities. As a result, operational efficiency is likely to soar, leading to increased productivity and better resource allocation. For the ICT department’s management, the artefact offers valuable insights and data-driven support for decision-making processes, facilitating more informed and well-founded choices. The anticipated improvements in service delivery, operational efficiency, and decision-making have the potential to create a positive and transformative impact on the case university's academic community.

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APPENDICES

APPENDIX A: Ethics Approval Letter

Cape Peninsula
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creating futures

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Office of the Research Ethics Committee
Faculty of Informatics and Design
Room 2.09
80 Roeland Street
Cape Town
Tel: 021-469 1012
Email: ndedem@cput.ac.za
Secretary: Mziyanda Ndede

08 November 2022

Mr Vusumzi Neville Funda
c/o Department of Information Technology
CPUT

Reference no: 200608029/2022/23

Project title: An Artificial Intelligence-enabled decision support system for South African higher education institutions

Approval period: 08 November 2022 – 31 December 2023

This is to certify that the Faculty of Informatics and Design Research Ethics Committee of the Cape Peninsula University of Technology conditionally approves the methodology and ethics of Mr Vusumzi Neville Funda (200608029) for Doctor of Philosophy: Informatics.

Any amendments, extension or other modifications to the protocol must be submitted to the Research Ethics Committee for approval.

The Committee must be informed of any serious adverse event and/or termination of the study.

Bmakwambeni

Dr Blessing Makwambeni
Acting Chair: Research Ethics Committee
Faculty of Informatics and Design
Cape Peninsula University of Technology

APPENDIX B: Permission to Conduct Research (CPUT)

Cape Peninsula University of Technology

Office of the Deputy Vice-Chancellor: Research,
Technology Innovation & Partnerships
Bellville Campus
P O Box 1906
Bellville 7535
Tel: 021-959 6242

08 November 2022

Mr Vusumzi Neville Funda
Student No: 200608029
Department of Information Technology
Faculty of Faculty of Informatics and Design
Cape Peninsula University of Technology

Dear Mr Funda

RE: PERMISSION TO CONDUCT RESEARCH AT CPUT

The Institutional Ethics Committee received your application entitled: "*An Artificial Intelligence-enabled decision support system for South African higher education institutions*" together with the dossier of supporting documents.

Faculty Ethics Committee Approval Date: 08 November 2022 (valid until 31 December 2023)

Committee Approval Reference No: 200608029/2022/23

Permission is herewith granted for you to do research at the Cape Peninsula University of Technology.

Wishing you the best in your study.

Sincerely

Prof Dina Burger
Director: Directorate Research Development
Cape Peninsula University of Technology

APPENDIX C: Permission to Conduct Research (UFH)

University of Fort Hare
Together in Excellence

University of Fort Hare
OFFICE OF UNIVERSITY REGISTRAR

Alice (Main) Campus: Private Bag X1314, King William's Town Road, Alice, 5700, RSA
Tel: +27 (0) 40 602 2501 • Fax: +27 (0) 40 602 2577• Email: akaturura@ufh.ac.za / registrar@ufh.ac.za
East London Campus: Private Bag X9083, 50 Church Street, East London, 5201, RSA

16th March, 2023

Mr Vusumzi Neville Funda
c/o Department of Information Technology
CPUT

Email: vfunda@ufh.ac.za

RE: Permission to Conduct Research at the University of Fort Hare.

We have considered your request for permission to a conduct research at the University of Fort Hare for a Doctor of Philosophy: Informatics project titled **"An Artificial Intelligence-enabled decision support system for South African higher education institutions"**

This letter serves to notify you that permission is hereby granted for you to carry out the research and to handle and utilise the data for this project as laid out in

- your request for this gatekeeper's permission,
- your research proposal,
- the site permission granted by CPUT
- the questionnaires submitted along with this request, and
- the stipulations under which ethical clearance for the study was issued by the **Research Ethics Committee: Faculty of Informatics and Design at CPUT**

Kindly be advised that beyond issuing this permission letter the Office of the Registrar is regrettably not in a position to assist with identification of and contacting participants, distributing and/or collecting questionnaires or any other related activities in the research process. You may directly contact the identified participants.

EN Zuma
University Registrar

APPENDIX D: Consent Letter

Cape Peninsula University of Technology

FID/REC/ICv0.1

FACULTY OF INFORMATICS AND DESIGN

Individual Consent for Research Participation

Title of the study:
An Artificial Intelligence-enabled decision support system for South African higher education institutions

Name of researcher:
Vusumzi Funda
Contact details: email: vusi.funda@gmail.com phone: 072 094 8642

Purpose of the Study:
The purpose of this study is to develop an AI-enabled decision support system for South African Higher Education Institutions.
Decision-making is a complex process within the university environment (Susnea, 2013). This process may entail operational resource allocation, student registration, enrolment, etc. The processes involved in decision-making require a timeous response and informed decisions to mitigate inconveniences on management, students and employees. The ITS department provides valuable tools and technologies for obtaining and analysing data. Given this complex nature, the ITS department often has to make informed and timeous decisions based on the large amounts of data generated from different faculties and departments (Manda & Dhaou, 2019). Currently, the selected HEI has a variety of information systems, operates in disconnected silos and generates large amounts of data which is complex to process using traditional approaches. Management and employees struggle to make informed and timeous decisions using traditional approaches, but AI tools could significantly help. Universities must adopt decision support systems that suit the institutions' infrastructure and plan, as this can impact the efficacy of DSS. Laudon and Laudon (2020) state that the adoption of AI tools into the decision-making process can assist organisations in dealing with generating Big Data.
Therefore, this study will develop an AI-enabled decision support system to support operational decision-making within the ITS department at a selected HEI in South Africa.

Participation: My participation will consist essentially of:

- Participating in completing an online questionnaire
- Taking part in face-to-face interviews that will be recorded and then transcribed

Confidentiality: I have received assurance from the researcher that the information I will share will remain strictly confidential unless noted below. I understand that the contents will be used only for the study indicated, and the outputs of this study will be conference presentations, journal articles and book chapters. My confidentiality will be protected by using general descriptors such as my current occupation, my age, and my gender.

Anonymity will be protected in the following manner:
A non-identification of respondents with their opinions in terms of the interview. In addition, for individuals to remain anonymous their personal details will not be required.

Conservation of data: The data collected will be kept in a secure manner.
The recordings will be downloaded and stored on a password protected external drive that will be stored in a locked drawer in a locked room. The transcripts will be saved as password protected word documents in a password protected folder on a password protected laptop.

Voluntary Participation: I am under no obligation to participate and if I choose to participate, I can withdraw from the study at any time and/or refuse to answer any questions, without suffering any negative consequences. If I choose to withdraw, all data gathered until the time of withdrawal will destroyed.

Additional consent: I make the following stipulations (please tick as appropriate):

	Yes	**No**
I would like my reflections to include my full name and surname		X
I would like to be a part of the recordings to be made of the engagement.	X	
My exact words may be used in publications	X	

Acceptance: I, (print name) PELISA MGEDEZI

agree to participate in the above research study conducted by Vusumzi Funda of the Faculty of Informatics and Design- ICT Department at the Cape Peninsula University of Technology.
If I have any questions about the study, I may contact the researcher. If I have any questions regarding the ethical conduct of this study, I may contact the secretary of the Faculty Research Ethics Committee at 021 469 1012, or email naidoove@cput.ac.za.

Participant's signature:..Date: 25 AUGUST 2022

Researcher's signature:..Date: 25 August 2022

APPENDIX E: Interview Questions

Interviews used to obtain participants' opinions and perceptions about the problem and to develop an prototype for Artificial intelligence-enabled decision support system

Interview RQ1

1. Can you describe the typical process for making operational decisions within the ICT department (or within your unit)?
2. How do you prioritize decision-making within the ICT department, and what factors are considered when determining which decisions require immediate attention versus longer-term planning?

Interview RQ2

3. Can you describe the role of stakeholder input in decision-making within the ICT department, and how it is collected and incorporated into the decision-making process?

Interview RQ3

4. How do you ensure that decisions made within the ICT department align with broader organizational goals and priorities?
5. How are data and analytics used to inform decision-making within the ICT department, and what metrics are typically used to evaluate IT systems and infrastructure?

Interview RQ4

6. What are some specific operational decision-making challenges that an AI-enabled decision support system could help address within the ICT department?

Interview RQ5

7. What kind of decision-making scenarios do you think the AI-enabled decision support system will be most useful for within the ICT department?

APPENDIX F: Questionnaire

Questionnaire 1

An artificial intelligence-enabled decision support system for South African higher education institutions

Demographic Information

1	Gender	Female	Male			
2	Age	>18-28	29-39	40-49	50-59	>60
3	Position	Admin staff	Technical staff	Supervisor	Manager	Director
4	Years in organisation	0 – 6 months	7 months – 2 years	3 years – 5 years	6 years – 8 years	9 years or more
5	Study level	High school	Undergrad	Honours	Masters	Doctorate

For each statement, please select a response that best reflects your opinion and experience.

#	No	**Statements** Please rank the following by crossing the most applicable. The weightings are: 1- strongly disagree, 2 – disagree, 3 – neutral, 4 – agree, and 5 – strongly agree					
*M*1	1	The system is easy to use	1	2	3	4	5
*M*2	2	The system helps me make decisions efficiently	1	2	3	4	5
*M*3	3	The system helps me make decisions quickly	1	2	3	4	5
*M*4	4	The system helps me make decisions effectively	1	2	3	4	5
*M*5	5	The system interface is easy to use	1	2	3	4	5
*M*6	6	System integrates existing decision-making processes or tools	1	2	3	4	5
*M*7	7	I am comfortable with the data being collected and stored by the system for decision-making purposes	1	2	3	4	5

#	No	**Statements** Please rank the following by crossing the most applicable. The weightings are: 1- strongly disagree, 2 – disagree, 3 – neutral, 4 – agree, and 5 – strongly agree					
*M*8	8	The system complemented the skills and expertise of ICT personnel	1	2	3	4	5
*M*9	9	I believe I have learned how to operate the system	1	2	3	4	5
*M*10	10	The system provides appropriate error messages and clear instructions of how to address errors	1	2	3	4	5
*M*11	11	The system improved optimisation of resource allocation	1	2	3	4	5
*M*12	12	The system minimised resource wastage	1	2	3	4	5
*M*13	13	I am satisfied with the system's speed and responsiveness	1	2	3	4	5
*M*14	14	The system provides information that helps me make decisions effectively	1	2	3	4	5
*M*15	15	The system assists me in my day-to-day tasks and responsibilities	1	2	3	4	5
*M*16	16	System's early detection of potential problems through predictive analytics positively impacted ICT operations	1	2	3	4	5
*M*17	17	System successfully predicted and prevented impending ICT issues before they escalated	1	2	3	4	5
*M*18	18	I have confidence in the system's predictive analytics for detecting potential future problems within the ICT operations	1	2	3	4	5
*M*19	19	The system provides easily understood information	1	2	3	4	5
*M*20	20	The system's chat feature assists me to make decisions	1	2	3	4	5
*M*21	21	The system has improved the quality of my decision-making process	1	2	3	4	5
*M*22	22	I would recommend the system to others for decision-making purposes	1	2	3	4	5
*M*23	23	The system had all expected functions and abilities	1	2	3	4	5
*M*24	24	Overall, the system is easy to use	1	2	3	4	5

#	No	**Statements** Please rank the following by crossing the most applicable. The weightings are: 1- strongly disagree, 2 – disagree, 3 – neutral, 4 – agree, and 5 – strongly agree					
*M*25	25	Overall, I am satisfied with the system	1	2	3	4	5

APPENDIX G: Goal Question Metric

Code	Metric	Weighted Statements
*M*1	User satisfaction levels	The system is easy to use
*M*2	Efficiency decision-making measurement	The system helps me make decisions efficiently
*M*3	Time efficiency comparison	The system helps me make decisions quickly
*M*4	Forecast success rate	The system helps me make decisions effectively
*M*5	Resource utilisation	The system interface is easy to use
*M*6	Data source incorporation	System integrates existing decision-making processes or tools
*M*7	Decision-making elements	I am comfortable with the data being collected and stored by the system for decision-making purposes
*M*8	Applicability assessment	The system complemented the skills and expertise of ICT personnel
*M*9	User training and usage	I believe I have learned how to operate the system
*M*10	Measurement of decision factors	The system provides appropriate error messages and clear instructions of how to address errors
*M*11	Effectiveness of ICT resource allocation	The system improved optimisation of resource allocation
*M*12	Resource allocation efficiency	The system minimised resource wastage
*M*13	System's accurate predictions	I am satisfied with the system's speed and responsiveness
*M*14	ICT department operational decision-making	The system provides information that helps me make decisions effectively
*M*15	Constructive decision impact	The system assists me in my day-to-day tasks and responsibilities
*M*16	Predictive accuracy	System's early detection of potential problems through predictive analytics positively impacted ICT operations
*M*17	Issue Prevention Rate	System successfully predicted and prevented impending ICT issues before they escalated
*M*18	Future problem detection	I have confidence in the system's predictive analytics for detecting potential future problems within the ICT operations
*M*19	Ease of Understanding	The system provides easily understood information
*M*20	Decision-Making Assistance	The system's chat feature assists me to make decisions
*M*21	User interface evaluation	The system has improved the quality of my decision-making process

Code	Metric	Weighted Statements
*M*22	System recommendation assessment	I would recommend the system to others for decision-making purposes
*M*23	Validity of system outputs	The system had all expected functions and abilities
*M*24	Decision-makers' usability assessment	Overall, the system is easy to use
*M*25	User experience feedback	Overall, I am satisfied with the system

APPENDIX H: SPSS Participants Responses

Inter-Item Correlation Matrix: Decision Support System

	Q14	Q19	Q20	Q22	Q23
Q14	1.000	0.340	0.303	0.403	0.365
Q19	0.340	1.000	0.327	0.498	0.179
Q20	0.303	0.327	1.000	0.606	0.290
Q22	0.403	0.498	0.606	1.000	0.248
Q23	0.365	0.179	0.290	0.248	1.000

Inter-Item Correlation Matrix: Efficiency

	Q11	Q12
Q11	1.000	0.553
Q12	0.553	1.000

Inter-Item Correlation Matrix: Integration

	Q8	Q9
Q8	1.000	0.371
Q9	0.371	1.000

Inter-Item Correlation Matrix: Scalability

	Q13	Q16	Q17	Q18
Q13	1.000	0.252	0.392	0.470
Q16	0.252	1.000	0.707	0.529
Q17	0.392	0.707	1.000	0.682
Q18	0.470	0.529	0.682	1.000

Inter-Item Correlation Matrix: User Satisfaction

	Q1	Q2	Q3	Q4	Q5	Q24	Q25
Q1	1.000	0.758	0.563	0.356	0.671	0.470	0.486
Q2	0.758	1.000	0.601	0.227	0.506	0.176	0.302
Q3	0.563	0.601	1.000	0.292	0.294	0.054	0.314
Q4	0.356	0.227	0.292	1.000	0.568	0.358	0.339
Q5	0.671	0.506	0.294	0.568	1.000	0.502	0.546
Q24	0.470	0.176	0.054	0.358	0.502	1.000	0.568
Q25	0.486	0.302	0.314	0.339	0.546	0.568	1.000

Mean and Standard Deviation Values of the Questionnaire

Item	SD (%)	D (%)	N (%)	A (%)	SA (%)	Mean (M)	Std. Deviation (SD)
Scalability							
I am satisfied with the system's speed and responsiveness	-	-	14,3	50,0	35,7	4.21	.686
System's early detection of potential problems through predictive analytics positively impacted ICT operations	-	3,60	14,3	53,6	28,6	4.07	.766
System successfully predicted and prevented impending ICT issues before they escalated	-	-	21,4	46,4	32,1	4.11	.737
I have confidence in the system's predictive analytics for detecting potential future problems within the ICT operations	-	-	17,9	50,0	32,1	4.14	.705
User Satisfaction							
The system is easy to use	-	-	25,0	53,6	21,4	3.96	.693
The system helps me make decisions efficiently	-	-	17,9	60,7	21,4	4.04	.637
The system helps me make decisions quickly	-	-	25,0	42,9	32,1	4.07	.766
The system helps me make decisions effectively	-	-	28,6	64,3	7,1	3.79	.568
The system interface is easy to use	-	-	32,1	50,0	17,9	3.86	.705
Overall, the system is easy to use	3,6	7,1	10,7	50,0	28,6	3.93	1.016
Overall, I am satisfied with the system	-	3,6	17,9	53,6	25,0	4.00	.770
Integration							

Item	SD (%)	D (%)	N (%)	A (%)	SA (%)	Mean (M)	Std. Deviation (SD)
System integrates existing decision-making processes or tools	10,7	3,6	25,0	35,7	25,0	3.61	1.227
The system complemented the skills and expertise of ICT personnel	-	3,6	14,3	46,4	35,7	4.14	.803
I believe I have learned how to operate the system	-	3,6	21,4	28,6	46,4	4.18	.905
I would recommend the system to others for decision-making purposes	-	3,6	32,1	42,9	21,4	3.82	.819
Efficiency							
The system provides appropriate error messages and clear instructions of how to address errors	7,1	10,7	39,3	25,0	17,9	3.36	1.129
The system improved optimization of resource allocation	-	7,1	10,7	60,7	21,4	3.96	.793
The system minimized resource wastage	-	3,6	14,3	53,6	28,6	4.07	.766
Decision Support (DS)							
I am comfortable with the data being collected and stored by the system for decision-making purposes	3,6	3,6	28,6	28,6	35,7	3.89	1.066
The system provides information that helps me make decisions effectively	-	3,6	28,6	50,0	17,9	3.82	.772
The system assists me in my day-to-day tasks and responsibilities	-	7,1	7,1	46,4	39,3	4.18	.863
The system provides easily understood information	-	7,1	25,0	32,1	35,7	3.96	.962
The system's chat feature assists me to make decisions	-	14,3	14,3	35,7	35,7	3.93	1.052
I would recommend the system to others for decision-making purposes	-	3,6	14,3	64,3	17,9	3.96	.693

Residuals Statistics[a]					
	Minimum	**Maximum**	**Mean**	**Std. Deviation**	**N**
Predicted Value	2.6679	4.5672	3.8878	.41930	28
Std. Predicted Value	-2.909	1.620	.000	1.000	28
Standard Error of Predicted Value	.095	.233	.149	.038	28
Adjusted Predicted Value	2.7623	4.5137	3.9031	.42105	28
Residual	-.75742	.57122	.00000	.33459	28
Std. Residual	-2.089	1.576	.000	.923	28
Stud. Residual	-2.361	1.652	-.019	1.019	28
Deleted Residual	-.96692	.62767	-.01531	.41061	28
Stud. Deleted Residual	-2.652	1.721	-.026	1.059	28
Mahal. Distance	.886	10.169	3.857	2.538	28
Cook's Distance	.000	.308	.047	.072	28
Centred Leverage Value	.033	.377	.143	.094	28

a. Dependent Variable: Decision_Support_System

Item	**SD (%)**	**D (%)**	**N (%)**	**A (%)**	**SA (%)**	**Mean (M)**	**Std. Deviation (SD)**
The system had all expected functions and abilities	3,6	14,3	21,4	53,6	7,1	3.46	.962

Coefficients[a]							
Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	95.0% Confidence Interval for B	
	B	Std. Error	Beta			Lower Bound	Upper Bound
(Constant)	.153	.689		.222	.826	-1.272	1.578
Scalability	.146	.155	.156	.938	.358	-.176	.467
User Satisfaction	.307	.197	.300	1.560	.132	-.100	.715
Integration	.036	.195	.035	.184	.856	-.367	.439
Efficiency	.468	.139	.599	3.375	.003	.181	.755

a. Dependent Variable: Decision_Support_System

ANNEXURE I: Editing Certificate

DR PATRICIA HARPUR

B.Sc Information Systems Software Engineering, B.Sc Information Systems (Hons)
M.Sc Information Systems, D.Technology Information Technology

Editing Certificate

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To Whom It May Concern

This document certifies I have copy-edited the following thesis by Vusumzi Neville Funda:

ARTIFICIAL INTELLIGENCE-ENABLED DECISION SUPPORT SYSTEM FOR SOUTH AFRICAN HIGHER EDUCATION INSTITUTIONS

Please note this does not cover any content, conceptual organisation, or textual changes made after the editing process.

Best regards

Dr Patricia Harpur

5 November 2023