A Decision Support Tool for Smart Campus Applications – An AUS Case Study

A DECISION SUPPORT TOOL FOR SMART CAMPUS APPLICATIONS – AN AUS CASE STUDY

by

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Declaration of Authorship

I declare that this thesis is my own work and, to the best of my knowledge and belief, it does not contain material published or written by a third party, except where permission has been obtained and/or appropriately cited through full and accurate referencing.

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Dedication

I would like to dedicate this thesis to the backbone of my life, my very loving & supportive family. ***Mummy, Papa, Fariyal and Amal;*** this one is for you!

Abstract

Since the last decade, advancement in the sciences around the world is causing an unstoppable incline towards smart technologies across multiple industries. Smart technologies come with numerous benefits ranging from reduced energy costs to productivity gains to lastly but very importantly, sustainability. One application of these smart technologies that attracts the objective of this thesis is “Smart campuses” which is basically the application of smart technologies to an educational institution. Few research provides the framework of the different available smart technologies that can be applied to a smart campus such as smart classrooms, smart transportation systems, smart operations and many more. However, applying all the available technologies at any campus would not be feasible in many institutes due to the various restrictions imposed by environment, culture and lack of funds, equipment, etc. Hence, this thesis involves development of a mathematical decision-making tool based on the Evidential Reasoning Approach for a successful implementation of smart applications to a university campus. The aim of this tool is to provide decision makers with rankings and utilities that enables them to decide on which smart applications (alternatives) are needed in the university based on certain inputs (attribute weights and beliefs at each evaluation grade). Upon building this tool, it was validated against 50 Truth data points from experts to analyze the quality of the tool. It was found that there is no statistically significant difference between the expert provided recommendations and the ones provided by the tool, even at a 0.05 significance level along with the area under ROC curve to be 0.734, depicting the tool performs as per expectations. Moreover, the tool’s performance evaluated using several metrics like accuracy, sensitivity etc. was upwards of 90% therefore further supporting the reliability of the tool. Lastly, the tool developed in this thesis is a generalized tool and hence can be used around the world with different number of alternatives and attributes by filling in the required inputs to the tool.

Keywords: Smart campus; Decision analysis; Technology; Evidential reasoning.

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List of Abbreviations

AHP	Analytical Hierarchy Process
AI	Artificial Intelligence
AR	Augmented Reality
ATD	Architectural Theory Diagram
AUS	American University of Sharjah
CA	Conjoint Analysis
CBR	Case-based Reasoning
CCTV	Closed-Circuit Television
DCE	Discrete Choice Experiments
DEA	Data Envelopment Analysis
DS	Dempster-Shafer
ER	Evidential Reasoning
FN	False Negative
FP	False Positive
GPS	Global Positioning Systems
IC	Implementation Cost
IDE	Integrated Development Environment
IM	Integrated Methods
IoT	Internet of Things
IT	Information Theory

MACBETH	Measuring of Attractiveness by a Categorically Based Evaluation Technique
MAUT	Multi-Attribute Utility Theory
MCDA	Multi-Criteria Decision Analysis
MCDM	Multi Criteria Decision-Making
MP	Mathematical Programming
NGT	Nominal Group Technique
PAPRIKA	Potentially All Pair-wise Rankings of All Possible Alternatives
PD	Project Duration
RFID	Radio Frequency Identification
ROC	Receiver Operating Characteristic
SAW	Simple Additive Weighting
SEM	Sustainable Energy Management
SGIS	Smart Geographic Information System
SLMS	Smart Learning Management System
SMART	Simple Multi-Attribute Rating Technique
TN	True Negative
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
TP	True Positive
VR	Virtual Reality
WSN	Wireless Sensor Network

List of Symbols

A	The set of basic attributes, which are measurable proxies of an abstract, general property *y*. $A = \{a_1, a_2, \dots, a_i, \dots, a_L\}$, where L is the number of basic attributes, and $i = 1,2, \dots, L$.
y	The general attribute one level above the basic attributes in the Architectural Theory Diagram (ATD).
E	The set of evaluation grades used to assess the attribute of an alternative. $E = \{\mathrm{e}_1, e_2, \dots, e_n, \dots, e_N\}$, where N is the number of distinct evaluation grades, and $n = 1,2, \dots, N$.
C	The set of alternatives. $C = \{c_1, c_2, \dots, c_p, \dots, c_Q\}$, where Q is the number of basic attributes, and $p = 1,2, \dots, Q$.
ω_i	The relative weight of the basic attribute a_i. The weights must add up to 1 across the basic attributes, thus, the weight of any basic attribute must be between 0 and 1, inclusive.
$\beta_{i,n}$	The degree of belief for the basic attribute a_i at the evaluation grade e_n.
$m_{i,n}$	The probability mass of a basic attribute a_i at evaluation grade e_n. It represents how well a_i supports the claim that the assessment of y is e_n.
m_i^*	The remaining probability mass unassigned to attribute a_i. It can be decomposed into two components: $\overline{m}_i$ and $\widetilde{m}_i$.
$\overline{m}_i$	The remaining probability mass unassigned to attribute a_i due to incomplete weight.
$\widetilde{m}_i$	The remaining probability mass unassigned to attribute a_i due to incomplete degree of belief.

$M_{j,n}$	Probability mass aggregated across the basic attributes a_1 to a_j at evaluation grade e_n.
M_j^*	Unassigned probability mass, aggregated over the basic attributes a_1 to a_j and all evaluation grades. It can be decomposed into two components: $\overline{M}_j$ and $\widetilde{M}_j$.
$\overline{M}_j$	Unassigned probability mass due to incomplete weight, aggregated across the basic attributes a_1 to a_j and all evaluation grades.
$\widetilde{M}_j$	Unassigned probability mass due to due to incomplete degrees of belief, aggregated across the basic attributes a_1 to a_j and all evaluation grades.
K_j	A normalization factor that ensures the aggregated probability masses remain between 0 and 1 in each recursion of the ER algorithm.
B_n	The aggregated degree of belief for the general attribute *y* assessed to the evaluation grade e_n.
B^*	The unassigned, aggregated degree of belief for the general attribute *y*.
u_n	Utility of an evaluation grade e_n.
U	The utility of the general attribute *y*.
$U_{\max}$	The maximum utility of the general attribute *y*.
$U_{\min}$	The minimum utility of the general attribute *y*.
U_{avg}	The average utility of the general attribute *y*.

Chapter 1. Introduction

1.1. Background

Smart cities have become an inevitable future asset due to the current global climate and ecological issues. There are many smart city technologies and frameworks to choose from, but not all would be feasible or optimal [1]. Furthermore, it would be costly to uproot an entire city's infrastructure for the sake of experiment. Therefore, testing smart applications on a smaller scale and in a realistic yet controllable environment, such as a university campus, might be the solution [2]. Not only is revolutionizing traditional campuses a step toward smart cities, but it would also be a significant aid to the strategic development of the educational sector and a major factor in its competitiveness.

1.1.1. The need for a smart campus

Smart campuses today could be models of smart cities in the future and a great representation of how cities will undergo high-tech makeovers to become smart using various cutting-edge technologies [3]. A university campus, in many ways, is a miniaturized city, especially if it is a fenced community. It enjoys a significant degree of independence from the surrounding city with its own security and centralized governance. A campus typically hosts educational, commercial, recreational, residential, and even religious functions within a limited area, thereby emulating the city it is surrounded by. Unlike cities, however, universities have fewer stakeholders. They have complete control over the necessary assets, such as the buildings and networks, and have a very receptive and adaptive audience in the form of students. Therefore, universities are uniquely positioned to experiment with new incoming technologies [3]. This implies that campuses can help the surrounding communities, regions, and cities progress by acting as a testing ground for different smart solutions to improve the socio-ecological aspects of the surrounding areas [4].

Since the 1990s, obtaining higher educational degrees has become the norm across many countries and cultures [5]. Due to this increased awareness and the constant effort by the education authorities to make higher education more accessible, there has been significant growth in the number of students [5]. This growth is concurrent with new innovative technologies reshaping several facets of human lives. Educational institutions, while being centers of learning and excellence, cannot afford to lag in developing and adapting to these new technologies.

To meet the needs of such a high number of students with different backgrounds, mindsets, interests, and preferences, universities must innovate and implement the latest technology on their campuses [6]. The challenge can also be seen as an opportunity for universities to experiment with different technologies in an overall attempt to increase student comfort and satisfaction.

Higher education is at a stage where it must undoubtedly grow through a digital shift. New students expect a more intuitive experience that fosters positive outcomes [7], and hence, smart campuses are starting to become the need of the hour. Educational institutions that are going to be considered the best by the end of the next decade are the ones that recognize the importance of true transformation using technology that enables frictionless and intuitive experiences [8]. A majority of the new students enrolling in universities were raised in a tech-driven, connected world [9]. This creates high expectations for on-demand experiences and opportunities for university stakeholders to invest in smart technologies for campus use. Moving forward, defining what makes a campus 'smart' is a must.

1.1.2. What is a smart campus?

According to Dong et al. [2], the definition of 'smart' is "very good at learning things, showing intelligent judgment, and fast reaction in handling problems. When a system can autonomously provide services in line with the dynamic user needs, it could be considered 'smart.'"

At this point, a few important distinctions are due. First, a smart *campus* utilizes *networked applications* to incorporate collaboration, use the current resources with higher efficiency, conserve resources, and eventually make the campus a very enjoyable place. A smart *application*, e.g., a chatbot, however, is based on one or more underlying *technologies*, e.g., Machine learning.

Smart applications can adapt and automatically modify behavior to fit the current environment. Recent information and communication technologies such as big data analytics, cloud services, the Internet of Things, and artificial intelligence, among others, are used to manage smart buildings, territories, and businesses [10]. In addition, smart applications leverage sensors, databases, and wireless access to collaborate with, sense, adapt and provide for users within an educational environment [11].

A smart campus can be deployed through multiple routes according to the financial capability of the university, the culture, location, background of the students, etc. Still, some major principles [12] need to be addressed to positively impact the stakeholder's experience upon implementing a smart campus.

Firstly, smart campus platforms should be intuitive and easy to use since students want to interact with systems that offer a great user experience without much effort. The higher the simplicity of the system, the higher its value. Great design can be achieved by deeply exploring the roles of the users, how each role interacts with the system, and the actual user experience. Moreover, there should be multiple ways of interacting with the platform via voice, touch, video, or gestures.

Secondly, the platforms designed for a smart campus should be modular, adaptive, and flexible since the needs of the campus and its users are ever-changing. Hence, the technology architecture approach should be to create software capabilities and solutions that are loosely connected and make the most out of the previously developed solutions. This approach offers the flexibility of morphing services while allowing software capabilities to be reused in any manner, permitting the campus to continue evolving.

Thirdly, the platform should be intelligent, which can be done by implementing artificial intelligence solutions on the campus. The large amounts of data created and stored due to all the interactions that various stakeholders had with the platform can be used to train AI-based solutions to make better predictions. The accuracy of these solutions should improve with every iteration and, hence, can provide the right stakeholders with the right information at the right time and place.

Lastly, the smart campus should facilitate collaboration with external stakeholders and universities worldwide since educational institutions are currently very local in their reach and scale. Hence, offering global scalability while making the most of the digital tools and technologies to provide positive data-driven experiences is one of the biggest aims of a smart campus. Any university transforming into a smart campus should try to abide by the previously mentioned principles.

Alnaaj et al. proposed a strategic framework for future smart campuses [13]. The authors carefully studied and proposed some models of the smart campus, as there is not just one way the transformation from a traditional campus to a smart campus can be carried out. They described the positive impact anticipated as a result of the implementation of smart applications, which extends beyond academics to waste and energy management, transportation, security, and several other areas within a university campus. However, deploying all the applications mentioned in [13] would be something beyond economic, financial, and cultural feasibility for the majority of the campuses around the world. This observation calls for a decision-making tool to make an informed decision based on the stakeholders' interests, which involves the management, students, faculty, and staff.

1.2. Problem Definition

Now that the importance and value of smart campuses have been highlighted, the next obstacle is which smart applications should be applied to a specific campus. The problem of choice establishes this dissertation's main theme, which focuses on designing a decision-making system consisting of a single decision-making tool or a combination of two or more decision-making tools in line.

There is ample research output in the field of smart technologies and cities. However, most available research is concerned with the technical feasibility of such proposed systems, and next to none address the problem of choice: Out of the tens of proposed smart technologies, which combination of smart applications would be optimal for a given campus? This question highlights a clear research gap whose existence is supported by [2], [14]. While many technically feasible applications are available in the market or the literature, not every application can be applied to every campus, as no one size fits all. Furthermore, other factors could restrict the implementation or operational success of a smart application, such as the location of the campus, the country's demographics, culture, religion, cost, assets, and others. Some examples of smart applications that could fail due to non-technical reasons include:

1. Using facial-recognition-enabled cameras to take attendance in classrooms may not work well in certain settings. For example, in some parts of the world, infectious respiratory diseases are widespread, and the population has adapted by wearing protective face masks in crowded and public places. Taking attendance through facial recognition would be a hassle for attendees who wear protective face masks. The same could be said for cultures where it is common for women to cover their faces as part of modest or religious attire.
2. Financial restrictions could stand in the way of implementing Virtual Reality (VR) and Augmented Reality (AR) applications in developing countries.
3. Even though blackwater can be purified to be safe enough for reuse as greywater or even potable water [15], [16], "there is still an issue of public acceptance" [17].

For those reasons, this thesis aims to develop a decision-making model that can be tailored to any campus. The proposed model should consider the different strategic success factors of a smart campus transition and recommend the optimal set of smart applications.

1.3. Research Aim and Objectives

Even though the concept of smart campuses has been around for a while now, there is no clear definition of a smart campus. Several papers and research discuss a smart campus only from a purely technical perspective [11]. However, an important aspect of how vital stakeholders such as students, faculty, staff, and university management perceive the value and use of a given smart application is usually overlooked. Hence, this study aims to identify the strategic success factors of a smart campus application and use the findings to develop a multicriteria decision support tool that helps key decision-makers consider the most academically, environmentally, and financially viable smart campus applications that meet the needs of vital stakeholders in their transformation to a smart campus.

This aim gives rise to the following research objectives:

1) Clearly define the hallmarks of a smart campus, i.e., technologies & applications

2) Understand the strategic success factors that govern the transition to a smart campus.

3) Select, design, and implement a strategic-level decision-making tool to aid a university's management in ranking the most worthwhile smart campus applications to implement, given the decision attributes and alternatives identified from the literature.

4) Validate the model and assess its performance.

To further dissect the above research objectives, we shall use the following questions to guide our efforts:

1) What defines a smart campus?
2) What strategic limitations stand in the way of transforming a traditional campus into a smart campus?
3) Given the scarcity of resources and the unique circumstances of each campus, how can the management team prioritize the smart campus applications to implement?
4) How reliable is the proposed decision-making tool?

In the next chapter, the first two research questions are addressed through an in-depth literature survey, while the third and fourth research questions are addressed in Chapter 3 and Chapter 4, respectively.

1.4. Thesis Organization

The thesis is organized as follows: Chapter 2 provides background about smart technologies, smart campuses, and the advantages of smart campuses through a literature survey. Chapter 3 presents a detailed review and discussion of applicable decision-making techniques, and the single most appropriate decision-making framework is selected. Next, a decision-making model is designed and developed mathematically and implemented in Python code. Chapter 4 covers the validation and performance assessment of the proposed model. Finally, Chapter 5 critically summarizes and concludes this thesis, considering possible future improvements and the implications of this work.

Chapter 2. Literature Review

This chapter surveys the state-of-the-art smart objectives, technologies, and applications available for educational campuses. In addition, the critical success factors for transitioning from a traditional campus to a smart campus are also explored.

2.1. Review of the State-of-the-Art of Smart Campuses

A smart campus utilizes smart technologies to create a seamless and intuitive experience for its users and provide them with up-to-the-minute services [13]. Multiple elements, such as people, processes, objects, screens, and services, function together to create a more immersive, interactive, and automated experience for all users: The students, staff, and faculty of a university or college institution [13]. The improvements brought about by a smart campus can be felt not only at the academic level but also at the financial, environmental, and social levels [4], [12].

2.1.1. Smart campus definition

The most practical method of defining a smart campus is by defining its objectives. A smart campus enables the development and eventual delivery of new business models and revenue streams [11]. Specifically, it can improve the following key areas of campus life: Workflow automation, safety and security, teaching and learning, communication and collaboration, strategic management, and resource conservation. The following benefits have enabled formerly traditional campuses to boast enhanced student learning, quality of life, lower operating costs, better safety and security, and improved environmental sustainability upon applying smart technology to their campuses [4].

2.1.1.1. Workflow automation

Smart technologies come with various benefits upon implementation, taking convenience to a new level. Since the advent of smart technology, several complex tasks can be performed simultaneously with minimal effort. These technologies are well equipped to analyze preferences to provide the user with the best automated and personalized services.

Elements such as smart cards and near-field technologies simplify repetitive tasks and transactions for students in terms of recording attendance and transaction processing times at campus restaurants, cafeterias, bookstores, etc. [4]. For example, these near-field technologies accommodate quicker check-out of books from a library or automatic deduction of funds upon exiting the restaurants for the meals consumed, hence saving valuable time. In addition, real-time occupancy systems, which come with smart campuses, allow students to see which specialized laboratories or computer labs are available to work in without walking all the way, thus saving students loads of time.

Moreover, IoT could be leveraged to improve numerous phases of the student and faculty experience, such as applying for and processing financial aid, scholarship, and student services, leading to a reduction in waiting times, mitigation of compliance mistakes, reduction in human errors, and the automation of several workflows.

2.1.1.2. Safety & security

Smart safety and security systems offer higher reliability than traditional systems. These systems enable automated, real-time preventive and remedial actions when a threat arises.

Smart security systems based on facial recognition and smart cards were found to enhance student satisfaction [18]. Furthermore, parents of potential students are also more inclined to choose universities with smart campuses for their children to ensure holistic development with the safety a smart campus possesses [18].

Peking University has cameras equipped with facial recognition technology installed at all its gates to scan the faces of all personnel entering the campus premises [19]. Such an application can save loads of time required to approve or deny access to the campus, which security guards would otherwise perform. Another well-known university in China, Beijing Normal University, uses voice recognition to grant access to students in their dormitories [19]. Many universities across the USA use smart technology to increase campus security and safety, such as networked video cameras, digitalized LED lighting systems, card readers, and geo-fencing, among the top technologies employed at various campuses across the United States. The University of Central Florida is planning to begin scanning license plates of cars entering or leaving campus to perform a variety of tasks, including monitoring vehicles entering the university, checking license plates against police databases, allowing cars to access respective parking lots, eliminating extra security guards, hangtags, parking stickers, and so on [19].

2.1.1.3. Teaching & learning

The continuous development of smart technology has paved the way to making teaching and learning processes more intuitive, productive, and motivating for students. It allows the campus to foster a digital culture by constantly collecting data that can be used to derive insights and later utilize them for the benefit of the users. These insights can provide contextual information to users based on their behaviors, intentions, and locations. One example could be guiding students by providing them with an insight-driven path toward their educational success. Another example could be providing faculty with the right information to interact positively with students, other faculty members, and the larger community. Newer, more interactive learning models are one of the greatest outcomes of smart campuses using relatively new technologies such as AR and VR.

Smart campuses have great potential for continuing quality education even if adverse situations arise, such as the current COVID-19 pandemic, which has delayed moving back to physical classes indefinitely. Professors and instructors now have many technological tools to effectively teach, even without being physically present, like in traditional courses. Smart technologies such as virtual labs, digital ports, and remote learning are great tools to foster operational resilience even in adverse circumstances.

Many universities, such as American University in Washington, DC [19], are using augmented reality (AR) and virtual reality (VR) to attract prospective students. These universities have complete campus tours that prospective students can access as campus experience, structure, and layout are vital aspects taken into consideration by students when choosing the university to enroll in. Besides virtual tours, immersive AR applications are great learning aids for different educational disciplines; hence, multiple universities are planning to employ them as a part of their curricula [3].

Some colleges, e.g., the UK-based Bolton College, are utilizing AI to design powerful digital assistants that can also answer students' questions with great accuracy and quality [19]. These assistants usually have a huge amount of information stored in their cloud and continuously keep learning from the large databases on the internet so that they can answer any question in a matter of seconds. Another university in Australia, Deakin University, has invested in an AI-powered digital assistant, too [19]. This assistant works as a part of an application called ‘Genie’ that informs students of their upcoming assignments, exams, various deadlines, and other tasks. The university plans to upscale the application using AI and big data to make the experience more personalized. For example, personalization would include the correct category of students being informed about related scholarship opportunities, local and international field-related seminars, competitions, etc. [19].

2.1.1.4. Communication & collaboration

Student collaboration on smart campuses is made simpler and more frequent due to integrated communication services that help students connect in many ways. A smart campus modifies how students interact with an institution by providing a more connected experience between the faculty, staff, and students, and, if required, even the parents. For example, every student can access conference tools and join collaborative sessions in no time. In addition, screen-sharing applications enable students to collaborate and work without requiring their physical presence.

2.1.1.5. Strategic management

Smart technologies use previously recorded data to understand and recommend improvements that can be made to increase the efficiency of the current systems [11]. Operational costs tend to decrease significantly when management decisions are driven by data instead of relying only on personal judgment [20]. A smart campus management platform would use strong analytical tools and rapid reporting capabilities to study and interpret information about resource utilization across the campus, student preferences, facility management practices, transportation demand and patterns across the campus, and travel patterns. The large integration and eventual interpretation of data collected over time aid educational institutions in increasing their efficiencies drastically, which was not possible previously.

2.1.1.6. Resource conservation

With the pressing need to make environmental sustainability a priority consideration in all decision-making stages, smart campuses rise to the occasion, as efforts to improve efficiency are often in line with resource conservation. In addition, smart technologies tend to regulate and automate energy use, saving loads of energy and money for the respective stakeholders.

Universities can leverage the benefits of a smart campus to constantly keep modernizing while meeting sustainability goals and staying relevant to their campus users. The most significant benefits that come with the implementation of smart technologies on campus are the considerable reduction in operational costs and increased efficiency through the smart use of electricity, transportation, and utilities. In addition, a decrease in water consumption, parking and traffic issues within the campus, and better utilization of space are also expected. These benefits not only increase campus users' satisfaction in the short term but also result in significant financial savings over the long term, which is an important goal for the economic stakeholders of the university [4], [21].

There are plenty of ways smart campuses maximize energy savings to conserve utilities. For example, a smart campus would use networked smart lighting with motion sensors to drive down energy usage during idle times. The data collected from motion sensors could help administrators identify usage patterns, which would help determine the critical areas of movement in which the lights must stay on most of the time and other areas where the lighting and air-conditioning can be switched off until needed.

Various smart technologies could aid in creating parking solutions that help students find parking spots in the shortest possible time, thus eliminating extra fuel consumption and reducing campus traffic created by students repeatedly circling to find a parking spot.

In summary, a well-rounded and comprehensive smart campus framework should address the six objectives outlined in this section. In the next section, the basic underlying technologies that support a smart campus solution are explored.

2.1.2. Smart campus technologies

Almost all available smart applications are based on four main technologies; namely, the Internet of Things (IoT), cloud computing, Augmented Reality (AR), and Artificial Intelligence (AI). They are pivotal for the successful transition from traditional campuses to smart campuses. Therefore, a brief review of these technologies is important to understand the state-of-the-art that will facilitate smart campuses' success.

2.1.2.1. Cloud computing

Cloud computing is the delivery of computing resources, storage space, or software such as servers, storage, databases, networking, software, and analytics over the internet, which can be addressed as "the cloud" [22]. These services offer the flexibility of resources and economies of scale with minimum interaction with the service provider.

With cloud computing, an organization typically only pays for the cloud services it uses, resulting in lower operating costs, more efficient local infrastructure operations, and the ability to scale up or down the resources subscribed to as per the organization’s demands [22], thereby relieving it from capacity planning pressure. In addition, a massive number of cloud services and resources can be made available to an organization with a few clicks and in a matter of minutes. As a result, cloud computing precludes the need for buying servers or data centers on-site, the associated capital expenses and maintenance costs, and the need for IT experts to manage an IT infrastructure owned and managed by the institution.

Compared to a single on-site data center, cloud computing services are run on a large network of globally distributed and secure data centers that are regularly upgraded, maintained and updated to the most recent generation of efficient computing hardware. Thus, cloud-based platforms are more reliable as they provide data backup and support business continuity and disaster recovery since the data is stored at multiple redundant sites on the cloud provider’s network. The organization’s data is not only protected from loss through redundancy but also from data breaches through comprehensive policies, access controls, and cyber security measures [4].

Due to the benefits mentioned above, cloud-based services are considered pivotal to the success of smart campuses. Cloud-based learning platforms allow learners to gain fast and low-cost access to online learning resources and services anytime and remotely, which wasn't possible with the conventional computational infrastructure. Also, cloud computing facilitates learning activities in an unstructured environment, providing infinite scalability and improved convenience. Using a cloud-based platform in a smart campus would allow users to access virtual learning materials at any time and share them seamlessly with other users.

2.1.2.2. Internet-of-things

As the term suggests, the Internet-of-things (IoT) extends internet connectivity to physical devices and everyday objects. These physical devices could be anything from something as small and simple as a light bulb to something as large and complex as an airplane. The connected devices can be set up to collect and share data in real-time via wireless networks and simple sensors [21]. IoT has numerous benefits, making it an indispensable technology in a smart campus [21]. It can provide an information platform that professors can use to track the student's learning progress and take appropriate actions if required. It can also automate several trivial operations on campus and allow stakeholders to focus more on learning processes. Furthermore, traffic, parking loads, electricity/water usage, air quality, and a ton of other parameters can be monitored with IoT [4].

2.1.2.3. Augmented reality

Augmented Reality (AR), as opposed to Virtual Reality (VR), is an interface technology that augments the view of the real world with digitally-created virtual content, such as visual elements, sound, or other sensory stimuli. Thus, AR allows a seamless overlay between computer-generated content and our real-world perceptions [23]. Often referred to as the next-generation interface, AR as a learning aid will enable students to gain in-depth understanding through hyper-realistic visualization. Apart from learning purposes, AR can also be used for campus navigation [24]. It can also contribute to smart campuses in security, communications, safety, etc.[4],[21].

2.1.2.4. Artificial intelligence

Artificial intelligence (AI) can be defined as the science by which machines learn from experience, adapt to new inputs, and generate solutions that would otherwise be very difficult to obtain using analytical techniques [25]. AI has recently gained popularity due to its significant success in pattern recognition, forecasting, planning, control, gaming, and other fields. Furthermore, with technologies such as cloud computing and IoT already added to a smart campus, AI can use them to foster positive outcomes for the different stakeholders involved in a smart campus.

From a learning perspective, AI can serve students, their instructors, and the university's long-term academic goals. AI could, for example, use student records to gauge their levels of understanding and specific areas of weakness and, consequently, customize the learning content for each student, making it specific to their needs, thus maximizing the quality of the learning process [26]. AI-based platforms can offer virtual tutors to teach students one-on-one while tracking their progress and providing instant feedback to keep them motivated with the learning materials. Accordingly, AI can also allocate students to instructors depending on the students' learning habits, soft skills, etc. From an instructor's point of view, AI helps identify strengths and weaknesses in teaching methods and suitable improvements to make the learning experience more efficient and valuable [27]. The AI would notify the instructor if multiple students were performing poorly in one specific area, allowing the instructor to pay extra attention to that topic and produce the needed outcomes from their students. Instructors these days do not need to create complete curriculums from scratch, as AI helps them with the provision of necessary educational materials, current trends, and important topics and brings to attention those difficult topics that students struggled to learn and master in the previous semester [14], [28]. AI could design solutions while being context-aware of the instructors' and students' psychological and emotional conditions [14].

From a campus management perspective, AI can assist with many services, such as transportation, maintenance, facilities management, procurement, finance, cyber and general security, safety, and overall university management [29].

The four main technologies discussed so far underpin almost all smart campus applications, which are surveyed in the next section.

2.1.3. Smart campus applications

To turn a traditional campus into a smart campus, it must use a set of smart applications. However, universities can hardly afford to establish all available applications simultaneously due to some unavoidable constraints. Therefore, the decision-makers need to pick certain applications from a set of alternatives to implement on their campuses. Based on our literature review [13], [14], [30]–[33], we concluded that the overwhelming majority of smart campus applications in the literature essentially fall into one of the following nine categories, which are described in the next subsections.

2.1.3.1. Smart learning management system

The Smart Learning Management System (SLMS) is a web-based learning platform that provides remote learning facilities for students and instructors [30]. Besides providing an educational environment, the SLMS also deals with course administrative tasks [30]. The SLMS offers an online storage facility to share course materials, course syllabi, project data, etc. It creates the class schedule and automatically tracks students' attendance while keeping track of the lectures and project tasks. The SLMS provides a collaborative research facility for the students and faculties. It removes the student-instructor communication constraints to improve the quality of education and to ensure customized learning that considers students' interests and weak points [13]. It also supports personalized learning and computerized adaptive testing with tailored questions and in-depth assessment [13]. Many researchers have advocated for implementing SLMS on university campuses due to its positive impact on the educational environment and quality [31]–[33].

2.1.3.2. Smart classroom

The "smart classroom" is a virtual atmosphere that replaces the physical classroom [14]. Unlike physical classrooms, the stakeholders can instantly share lecture sheets, slides, and video content. The smart classroom encompasses an online face-to-face learning facility, a whiteboard, and a text and image-sharing clipboard. It provides tracking and recording options for students and faculty. Students can record the lectures to watch offline. It is a web-based solution accessible from all smart devices, including desktop computers, smartphones, and tablet computers. In addition, the smart classroom utilizes VR applications for experiments and simulations [13]. Because of advanced educational facilities, many policymakers suggested integrating the smart classroom with the physical education system [31]–[33], [34]–[36].

2.1.3.3. Smart campus operations

Smart campus operations assist stakeholders in carrying out administrative tasks on campus [13]. For example, the smart operation uses a smart card to access the meal and library facilities. The smart card can also be used for automatically recording class attendance and laboratories as it would hold the user's detailed information and, thus, can be used for on-campus payments [13]. ‘Smart operation’ could also comprise a smart library management system with a smart authentication tool. For example, RFID tags on library material books automate library services, such as independent book borrowing and returning, book searching, and tracking [37].

2.1.3.4. Smart administrative system

A smart administrative system is a web-based solution that automates administrative operations. Students who use smart administrative systems can complete admission and registration online independently of their physical presence on campus [13]. The smart administrative system simplifies administrative tasks such as managing official communications, scheduling teleconferences, videoconferences, and review meetings [14]. All administrative support, e.g., providing information to the students, parents, or faculties, can be fully automated with AI-powered applications. Financial management activities, such as annual campus budgeting, balance sheet management, activity planning and budgeting, and financial transactions, can be done through automated administration systems [14],[31]. The smart administration system also covers the report generation on financial growth, investment, donation, and returns on assets [38].

2.1.3.5. Safe learning environment

Ensuring a safe learning environment is one of the most crucial objectives of a smart campus. Therefore, researchers argued for adapting technologies to ensure safety on the varsity campus [22],[39],[40]. A safe learning environment can be supported by using

24/7 surveillance cameras. A computer vision application could analyze the real-time feed captured by the surveillance cameras, continuously scanning for physical threats [13]. Besides AI-enabled surveillance cameras, the authentication system could also be automated to improve the access control facility on the campus [31].

2.1.3.6. Smart geographic information system

A Smart Geographic Information System (SGIS) can be defined as a system that is designed to provide geographic data to manage and monitor campus spaces and assets more efficiently, intuitively, and comprehensively. The SGIS involves advanced technology like GPS, WSN, or RFID to accurately locate campus facilities [14]. In addition, the SGIS ensures smart navigation for students and visitors to specific locations or offices. The SGIS also incorporates a digital map and VR application to help visitors find available facilities like kiosks, an office, a library, or dorms [13].

2.1.3.7. Waste and water management

One of the most important preconditions for a campus to turn into a smart campus is the availability of purified water and waste management systems [37], [41]. The campus water and waste management systems ensure a healthy environment. The smart campus should monitor and report water and waste levels with the help of sensors [14]. The real-time water and waste status monitoring system can draw the decision-makers' attention to take the necessary steps for unacceptable contamination levels. The smart campus should also have IoT-based smart technologies to maintain the smart bathroom, which is a bathroom that automatically detects water usage and wastage and effectively manages them using RFID to read and analyze the water level continuously. It then reports the consumption levels to the users [14].

2.1.3.8. Sustainable energy management

Sustainable Energy Management (SEM) can be defined as the responsible management of energy in such a way that the consumption needs of the current and future generations are not compromised [42]. Sustainable building design, smart street lighting, solar power, etc., support sustainable energy usage [13]. A sustainable building must have an automated energy-saving system. The building should have sensors and other IoT-based technology to automatically power on or off the air conditioning, heating, light, fan, or other electronic devices based on the activity levels and the number of occupants [13], [14]. The temperature, humidity, and CO_2 levels on campus should also be tracked to continuously improve air quality [32] and energy consumption patterns.

2.1.3.9. Smart transportation system

Smart transportation provides various modes of transportation and traffic management that strive to ensure a safe and coordinated traffic network. To enable fleet tracking on campus, RFID and IoT-based technologies are used [13], [43]. For example, a smart parking system can provide optimal parking services to students and visitors [14]. The smart parking system can be established with multiple CCTV cameras and sensors that continuously notify of the availability of the parking slots while assuring the best management of the parking spaces.

Despite the countless smart campus applications available in the literature and commercially, we believe they could all be classified by function into one of the nine families of solutions outlined in this section.

In an attempt to address the first research question, “What defines a smart campus?” the hallmarks of a smart campus have been precisely determined by enumerating its objectives and underlying technologies and broadly categorizing smart campus solutions into nine distinct functional families.

To address the second research question, “What strategic limitations stand in the way of transforming a traditional campus to a smart campus?” we revisit the literature to uncover the critical success factors in the anticipated transition of traditional campuses to smart campuses.

2.1.4. Critical success factors

A decision problem cannot be fully defined without attributes. Therefore, the decision problem is decomposed into its basic attributes to develop a decision support system. Six decision attributes for this study were chosen based on the recommendation of numerous pieces of literature. Those attributes are (1) implementation cost, (2) operation cost, (3) maintenance cost, (4) project duration, (5) stakeholder’s benefit, and (6) resource availability.

2.1.4.1. Implementation cost

The implementation cost is the most important success factor for introducing new technology on a university campus [44],[45]. Intuitively, decision-makers studying the feasibility of a new technology must perform a cost-benefit analysis, in which the implementation cost is a principal cost element [44],[46].

2.1.4.2. Operation cost

Operation cost can be defined as the cost of running a system after its implementation. The operation cost includes, for example, expenses for staffing, electricity, storage rental, and security. If the operation cost of any system is estimated to be too high, the rationale for implementing it becomes too low. So, the operation cost directly affects the alternative selection process while applying the new technology on a university campus [47],[48].

2.1.4.3. Maintenance cost

Maintenance cost [49],[50] is also one of the most important cost elements in any investment analysis. Like operation cost, maintenance cost is a determiner of any asset's economic life.

2.1.4.4. Project duration

The extent to which decision-makers find a technology appealing is influenced by how long a project will take to be fully functional. Therefore, project implementation duration plays an important role in developing a decision-making tool [45]. Generally, faster implementation times increase the attractiveness of an alternative.

2.1.4.5. Stakeholder's benefit

The desired outcome of the highest priority of developing a smart campus is maximizing the benefits of its stakeholders, where the stakeholders of a smart campus include not only students but also staff, faculty, and the management team[1]. If

[1] The anticipated roles and contributions of each stakeholder category in the smart campus transition are discussed in Appendix B

stakeholders' benefits are measured or expected not to exceed the system's costs, then it should not be implemented. Therefore, expected stakeholder benefit is one of the most important attributes of the considered decision support system [51],[52]. The benefit to the stakeholders may be estimated based on the financial benefits of implementing a system, i.e., savings or even cash inflows. Still, in the case of a smart campus, some types of stakeholders may only derive satisfaction from using the system rather than witness any cash inflows or savings. Where stakeholder benefit cannot be measured in financial terms, it is alternatively measured in terms of utility.

2.1.4.6. Resource availability

New technology on the university campus can only be advocated if the university can acquire sufficient funds to invest in its development [48],[53],[54]. Therefore, the availability of resources is another critical success factor.

2.2. Conclusion

This chapter summarized the deductions made from an in-depth literature survey that sought to clearly define a smart campus in terms of objectives, technologies, applications, and strategic success factors. Six objectives, four main technologies, nine functional families of applications, and six critical success factors have been identified. These findings will guide and inform subsequent efforts to define the parameters of an optimization problem. The selection and construction of a working decision-making model are discussed in the next chapter.

Chapter 3. Methodology

3.1. Introduction

This chapter outlines the research methodology for this thesis and the decision-making techniques appropriate for this problem. First, a critical comparison of those decision-making techniques is laid out, followed by a nomination of the most suitable decision-making technique to move forward with. Next, we review different weight allocation methods for the suggested decision tool, with a justification of which weight allocation method best fits this research problem. Finally, the decision model is formulated mathematically and implemented in Python using the PyCharm development environment.

3.2. Research Methodology

In the previous chapter, a literature review has partly addressed some research questions. To adequately address the first research question: "What defines a smart campus?" we surveyed the literature for the definition of a smart campus and its primary technologies and applications. Furthermore, the surveyed smart-campus applications were categorized into nine families by function. To validate the proposed categorization of smart campus applications, a stakeholder opinion survey was conducted at AUS. Suppose stark differences in preference exist between the nine functional families. In that case, it can be inferred that most respondents understood the categories to be separate and independent, implying that the categorization is valid in terms of being distinct and non-overlapping. Before conducting the survey, nonetheless, we must verify that stakeholders at AUS believe there is a need for a smart campus. This is indeed the case according to the recent research findings of Abu Alnaaj [55, p. 72], who conducted his survey research at AUS as well. According to his survey results, 50% of respondents were unhappy with the campus' current features, and 46% voted that it is important to have a smart campus. Picking up from where Abu Alnaaj left off, we asked respondents how much they preferred each of the nine functional families compared to the others.

To address the second research question: “What strategic limitations stand in the way of transforming a traditional campus into a smart campus?” a further literature survey was conducted to uncover the critical success factors at the strategic level.

The third research question, “How can the management team prioritize the smart campus applications to implement?” requires building a decision-making model to be used by a university’s strategic management team. Therefore, families of Multi-Criteria Decision-Making (MCDM) methods have been reviewed. Based on the nature of the problem at hand, one MCDM framework should be selected and consequently implemented in a programming environment.

Taking the nine functional families of smart campus applications as the model’s alternatives and the six critical success factors as the decision-making attributes, an essential pillar of any MCDM problem is determining the relative weights of the attributes, which express the attributes’ relative importance. Since AUS is considered the testing ground for the proposed model, a group of experts at AUS (referred to herein as Group A) participated in a semi-structured group interview as part of the Nominal Group Technique (NGT), where they were asked to recommend the weights of the different attributes. Group A included faculty, staff, and operational managers at AUS.

With alternatives, attributes, and attribute weights fully defined, the model is ready to supply an output (in the form of a prioritized set of alternatives) given the input variables. To validate the model, 50 decision-making scenarios were randomly generated and run through the model to generate 50 outputs. The same 50 input sets were supplied to another group of decision-making experts external to AUS (referred to as Group B), who used their experience and judgment to recommend the optimal alternatives given each input scenario. Thus, the experts provided 50 truth data points against which to compare the 50 outputs from the system. Should the differences between the model and expert recommendations be statistically insignificant, the model would be deemed valid, and performance assessments would be conducted as the final step of this research work that concludes the answer to the last research question.

Based on the ‘Research Onion’ model by Saunders et al [56], our research methodology can be described on the following dimensions:

- ***Philosophy***: The perceptions and attitudes of the stakeholders and experts were significant inputs to this work. Furthermore, the researcher has made some subjective choices regarding the grouping of alternatives, the choice of the MCDM method, and the decision attributes. This implies a subjectivist ontology and axiology. However, once the attitudes and opinions of the stakeholders and experts were coded into numbers, the researcher focused on objectively building and testing the model, with the intention of generalizing the use of this model to other universities. From that point onwards, a good quality model is taken to be any model that accurately emulates an expert regardless of the researcher's own opinions and views, implying an objectivist epistemology. Since the research philosophy here is neither entirely interpretivist nor positivist, it could very well be pragmatist by exclusion.

- ***Approach***: In surveying the literature, the researcher looked for patterns and groups of smart campus alternatives and critical success factors through inductive reasoning. Next, it was hypothesized that the developed model is appropriate for guiding a smart campus transformation, and data was subsequently collected to test this hypothesis. This theme is typical of a deductive approach. Hence, the research approach could be described as abductive since the researcher engaged in theory-building and testing.

- ***Purpose***: The purpose of a study can be inferred from the types of research questions. The first two research questions are exploratory, but the third is explanatory, as it invites building a decision-making model whose purpose is to establish a relationship between stakeholder beliefs and the optimal course of action. Thereafter, the fourth and last research question is evaluative, attempting to determine how well the model works. Thus, we have a so-called 'combined study' as it combines more than one purpose [58, p. 176]

- ***Strategy***: Three research strategies have been utilized in this work:

    - Surveys (of the literature, as well as a questionnaire to validate the coding of the surveyed smart campus applications),
    - Semi-structured interviews (to elicit attribute weights),
    - Experiment to test the hypothesis that the model reliably emulates decision-making experts. Here, the test 'subjects' are 50 randomly generated sets of inputs. One 'treatment' would be the processing by a human expert, and the other 'treatment' is the processing by the proposed model. The output is the recommended smart campus application, which is observed after both treatments and compared. This is a within-subjects design since all subjects go through the two treatments.

  The first two strategies (questionnaire and interviews) were executed in AUS campus as part of a case study. Therefore, it can be argued that there are just two research strategies: A single, holistic case study and an experiment since a case study allows for mixed data collection methods. Furthermore, the experiment was conducted with the input of experts external to AUS to eliminate bias and avoid conflicts of interest. Thus, the experiment should not be considered part of the case study.

- ***Choice***: This is a mixed methods strategy as a qualitative method, namely semi-structured interviews, and a quantitative method, namely the questionnaire, have been used.

- ***Study Design***: This is an embedded mixed-method design, as each research question is a precursor to the next.

So far, the review of smart campus definitions, technologies, and applications in the literature has contributed to the first research objective. The following sections of this chapter address the second and third research objectives, starting with an overview of decision-making frameworks. The upcoming section reviews the different decision-making frameworks in the literature.

3.3. Review of Decision-Making Techniques

Decision-making is vital in any industry and is considered the primary function of any management team. A decision is a course of action chosen purposefully from a set of alternatives to achieve and maximize organizational or managerial goals. Similarly, decision-making is a process that involves the selection of a course of action from among two or more possible alternatives to solve a given problem within a given time frame [39]. The appropriate decision-making process allows the organization to grow in multiple directions, and each decision-making process seeks a set of goals. These goals could be pre-set business objectives, missions, or sections of the long-term vision. To fulfill these goals, organizations face many obstacles in the administrative, marketing, operational, and financial domains; hence, decision-making processes are appropriately used to satisfy these goals [42]. A decision-making process can be broken down into the following six steps [57]:

1) Classify and define the problem
2) Gather information and collect relevant data
3) Enumerate and score all possible alternatives
4) Choose the best alternative
5) Create the plan and execute it
6) Test the validity and effectiveness of the decision

There are broadly three levels of decision-making for any project: Strategic, tactical, and operational [58],[57]. Decisions at the strategic level form the basis for the decisions to be made at the other two levels and tackle long-term goals, visions, and values for overall development. The tactical level considers the medium-term decisions to achieve the results specified at the strategic level. This level here would address the development of infrastructure in terms of space and people required to lead the transformation from a traditional campus to a smart campus. The last operational level addresses the short-term vision, which also involves the implementation of goals and the execution of the different applications needed for campus transformation [59]. Depending on the decision-making level, some decision-making techniques would be more suitable than others. In this thesis, we restrict ourselves to decision-making at the strategic level, and in the next section, we explore those techniques that are best suited for strategic decision-making.

3.3.1. Types of decision-making techniques

According to the literature, the decision-making methods can be broken down into four major categories: Multi-Criteria Decision-Making (MCDM), Mathematical Programming (MP), Artificial Intelligence (AI), and Integrated Methods (IMs).

An MCDM technique is typically a multi-step process consisting of methods to structure and execute a formal decision-making process. These allow the decision-maker to find the best among a set of multiple alternatives by assessing different alternatives against various criteria.

Mathematical Programming (MP) methods usually optimize objectives while considering multiple constraints and other boundaries within which the stakeholders must make an appropriate decision. Goal programming, linear programming, and stochastic programming are famous MP methods.

AI-based methods are based on self-learning models that can perform regression and classification on new data by learning from historical data. These models work in real-time to make predictions and give recommendations accordingly [20].

Lastly, an IM combines any two methods belonging to different categories to reap the advantages of both and mitigate the disadvantages of any one method. Hence, some researchers recommend making critical decisions using an IM [59]. However, MCDM is best for making decisions at a strategic level and - in specific - for smart campus applications as it incorporates various criteria that might be conflicting in nature. Therefore, MCDM is the way to go as it enables decision-makers to solve conflicting real-world quantitative and qualitative multi-criteria problems and to find best-fit alternatives from a set of alternatives in uncertain and risky environments [60].

3.3.2. Multi-criteria decision-making methods

According to Belton and Stewart, MCDM is an “umbrella term to describe a collection of formal approaches which seek to take explicit account of multiple criteria in helping individuals or groups of individuals to explore decisions that matter" [61]. In other words, MCDM can be considered a particularly useful framework in situations with multiple and conflicting criteria that the stakeholders and the decision-makers value differently. Thus, MCDM aids in evaluating the several possible courses of action with respect to criteria that account for the key dimension of the decision-making problem involving human preferences and judgment. Due to this clear advantage that MCDM allows, it has gained significant traction and usage over the last decades. MCDM methods are also considered integrative evaluation (IM) methods because they combine information about the performance of each alternative with respect to criteria, along with subjective judgments about the relative importance of the various evaluation criteria in a decision-making context.

There are plenty of MCDM methods discussed in the literature; hence, briefly understanding the categorization of these methods is helpful before reviewing the individual methods in depth. The specialists of the multi-criteria decision-making society have divided the various MCDM methods into three categories to facilitate the selection of the appropriate method based on the type of problem. Roy [62] classified the MCDM methods as follows: Unique criterion approach, outranking synthesis approach, and interactive local judgment [63].

The outranking synthesis approach deals with developing an outranking relationship in which the decision-maker's preferences are represented, and the relationship is explored to help the decision-maker solve the problem. Examples of this approach include ELECTRE and PROMETHEE.

The interactive local judgment approach deals with methods that alternate between calculation steps and dialogue steps. The calculation steps give successive solutions, and the dialogue steps provide an additional source of information on the decision-maker's preferences [58], [64].

Lastly, the unique criterion approach, which we believe could be the most appropriate for the smart campus decision problem, deals with aggregating the different interests, opinions, and required parameters into an objective function that will be optimized.

Examples of this approach include Multi-Attribute Utility Theory (MAUT), Simple Multi-Attribute Rating Technique (SMART), and Analytic Hierarchy Process (AHP).

The following sections explore the strengths and weaknesses of each of the different MCDM methods. The methods considered were gathered from a review of [62], [65]–[67] and hence considered to be the popular ones for MCDM.

3.3.2.1. Multi-Attribute Utility Theory (MAUT)

MAUT is a method that gives out the best course of action for a decision-making problem by assigning a utility to each possible outcome and calculating the best outcome based on the highest utility. The advantages of MAUT include its ability to take uncertainty into account and incorporate the decision-makers' preferences into the problem. Its disadvantages are that MAUT is a data-intensive method, and the preferences provided need to be precise for this method to work properly [67].

3.3.2.2. Simple multi-attribute rating technique (SMART)

SMART is one of the simplest forms of MAUT. It functions on two main assumptions: Utility independence and preferential independence. These two assumptions then permit the convenient conversion of importance weights into actual numbers. SMART's pros include the method's simplicity, allowance for any weight assignment technique, and less effort required by decision-makers. However, this procedure may not be convenient considering the complex framework of real-life decision-making problems [67]. In real life, the criteria affecting the decision-making process are usually inter-related; hence, this simplistic approach only works when very minimal data is available.

3.3.2.3. Analytic hierarchy process (AHP)

AHP is a method that gives a solution to a specific decision-making problem using a pairwise comparison between the different alternatives and criteria. It also heavily relies on experts' judgments to obtain priority scales. AHP's advantages include easy application, not being data-intensive, and scalability to work with different-sized problems. The disadvantages of this method are the risk of rank reversal (a problem that can be caused due to the interdependence between criteria and alternatives) and inconsistencies between judgment and ranking criteria [12], [21], [22], [68].

3.3.2.4. ELECTRE

ELECTRE is an iterative outranking method based on concordance analysis intending to outrank the best solution for a specific decision-making problem. Its advantages include the method's ability to consider uncertainty and vagueness. However, the outcome is not easy to explain in layperson's terms and requires a complex level of understanding to study and analyze the output. Also, the strengths and weaknesses of the alternatives cannot be clearly identified due to the outranking technique of this model [67].

3.3.2.5. PROMETHEE

PROMETHEE is also an outranking method like the ELECTRE and performs several iterations to solve the decision-making problem. However, it has several versions for partial ranking, complete ranking, and interval-based ranking of the different alternatives in the decision-making problem. PROMETHEE also has other variations for ranking the alternatives when the set of viable solutions is continuous, with segmentation constraints, and one for the human brain representation. This method is easy to use and does not force an assumption that the criteria are proportionate. The disadvantage of this method is that it does not provide a clear method by which to assign weights to the different criteria [67].

3.3.2.6. Fuzzy set theory

Fuzzy set theory is a very useful tool for describing a situation in which the data are imprecise or vague. Fuzzy sets handle such situations by attributing a certain degree to which a certain object belongs to a set. Basically, fuzzy set theory is an extension of the classical set theory that facilitates solving problems related to dealing with imprecise and uncertain data. Its advantages include allowing for imprecise input and accounting for insufficient information. However, it is very difficult to develop and can require multiple simulations before use [67].

3.3.2.7. Case-based Reasoning (CBR)

Case-based reasoning (CBR) method retrieves cases similar to the current decision-making problem from an existing database of cases. It then proposes a solution to the current problem based on previous solutions to the most similar cases. CBR is not data intensive like AHP, requires very little maintenance, could be improved over time, and can adapt to environmental changes. However, the issue with CBR is that it is sensitive to inconsistent data and requires many cases to provide the user with a good solution to the current decision-making problem [67].

3.3.2.8. Data envelopment analysis (DEA)

Data Envelopment Analysis (DEA) measures the relative efficiencies of alternatives against each other, with the most efficient alternative having a rating of 1 and the other alternatives being a fraction of 1. It uses linear programming to perform these measurements of relative efficiencies. DEA's pros include its capability to handle multiple inputs and outputs. Moreover, the efficiency of this method can be analyzed and quantified. However, this method cannot deal with imprecise data since it assumes that it has complete input and output information [67].

3.3.2.9. Goal programming

Goal programming is a pragmatic programming method that can solve a decision-making problem from infinite alternatives. Its advantages include the method's capability to handle large-scale problems with infinite alternatives. The disadvantage of this method is it needs to be used in combination with other MCDM methods to determine the weight coefficients [67].

3.3.2.10. Simple additive weighting (SAW)

SAW is a value function established based on a simple addition of scores representing the goal achievement under each criterion, multiplied by particular weights. The advantages include the method's ability to compensate among criteria, being simple to use, and not requiring complex computer programs as the calculations are very trivial and simple. However, the estimates provided by this method may not always reflect the real situation, and the result might not look logical [67].

3.3.2.11. Technique for order of preference by similarity to ideal solution (TOPSIS)

In a nutshell, the TOPSIS method is a method for identifying two alternatives: One alternative is closest to the ideal solution, and the other alternative is the farthest from the ideal solution in a multidimensional computing space. This method is easy to use, and program and has a simple process. Also, the number of steps required to obtain the solution remains the same regardless of the number of attributes. This method's disadvantages include relying on Euclidean distance to obtain the solution, which ignores the correlation of the attributes, and the difficulty of weighing the final judgment and maintaining its consistency [67].

3.3.2.12. Evidential reasoning (ER)

The Evidential Reasoning (ER) approach is a hybrid decision support framework that provides solutions to multi-criteria decision analysis problems [69], [70]. It is a hybrid decision framework that encompasses the utility theory [67], [71], probability theory [72], and theory of evidence [73], [74].

The ER approach can make decisions in critical situations where qualitative and quantitative criteria may coexist [75]. The ER approach uses a belief structure to capture uncertainties in the decision-making process. To define any decision problem, the ER decomposes the problem into its basic attributes and combines their evidence. The ER approach has two basic parts: The knowledge base and the inference engine.

The knowledge base defines the domain knowledge of the decision problems. In addition, it considers the decision parameters and additional decision-making factors like weights of the attributes and beliefs of the users [76], [77]. The inference engine of the ER approach is constructed based on the Dempster-Shafer (DS) theorem [73].

The ER approach uses different evaluation grades to define the probability of an alternative. A belief is considered against each evaluation grade, and a probability mass is generated for the attributes. While calculating probability masses, the ER also computes the uncertainty associated with the system. Based on the probability masses, the DS theory combines the beliefs of the basic attributes under a general attribute, which results in the degree of belief in the general attributes. Finally, using utility theory, ER provides the utility of an alternative. The optimal solution to a multi-criteria decision analysis problem can be deduced by comparing the utilities of different alternatives. To summarize this section, the types of MCDM techniques can be hierarchically described in Figure 1.

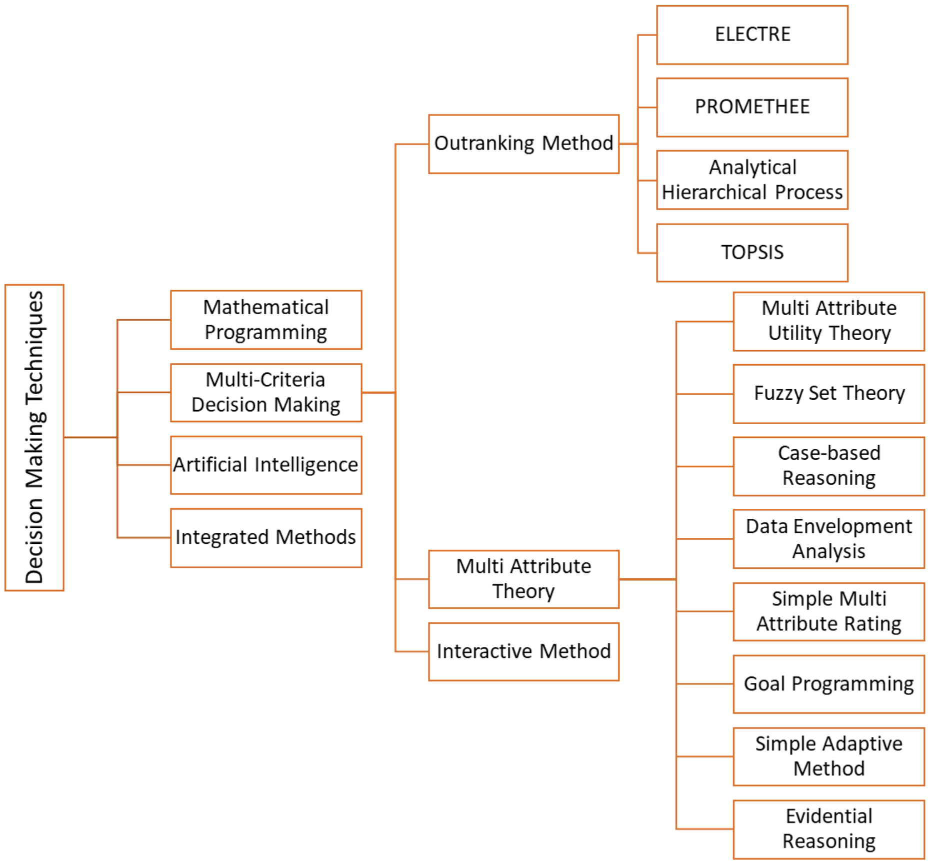

Figure 1 Hierarchy of decision-making techniques

Practically, decision-makers rarely have access to complete information before making a decision. Incomplete information in the decision-making process raises some uncertainties, which could misguide the inference engine into recommending unsuitable alternatives. As noted previously, many of the available decision support frameworks do not provide an efficient mechanism to handle these uncertainties. Given the recency of research in strategic decision-making for smart campuses, there are many sources of uncertainty involved, as there would be instances where the university might not have access to all the data required or even have the data in the first place to make the decision. For this reason, we shall restrict ourselves to MCDM methods that can tackle input uncertainties: MAUT, ELECTRE, Fuzzy set, and ER.

In addition, the data that would be collected to make sound decisions would have different types and scales. This is not only the case in the context of this thesis, as several complex strategic decision-making processes involve collecting data of various types. Some decision variables would be quantitative such as costs, return on investment, project duration, etc., and others would be qualitative, such as stakeholders' opinions on applications, stakeholders' requirements, etc. These different data types must be transformed to a common scale with a suitable format before they can be used to make decisions. Even though most available decision frameworks can handle both data categories, the transformation of qualitative data to quantitative data may result in distortion of the qualitative input. In the case of qualitative data, the available frameworks use a data conversion process [77], [78]. In this process, the model directly assigns some value to the evaluation grade, which hardly reserves the evaluation precision.

Luckily, the ER approach addresses each of the above challenges. The ER method works efficiently even if one of the below situations arises, giving it an edge over its rivals [79]:

1. **Integration of qualitative and quantitative data:** The ER approach can handle both qualitative and quantitative attributes. It incorporates judgments from domain experts that assist with data transformation as the task is domain specific [80]. All variables are strategically transformed into a common scale for decision-making.
2. **Avoiding distortion of qualitative data during transformation:** To solve this data handling issue, the ER approach introduces a new data acquisition concept: The degree of belief [75], [74], [76]–[78]. The concept of degrees of belief proposed by the ER approach offers the most suitable way of describing and dealing with the uncertainty that comes with the decision-making regarding smart campus applications. It accounts for the degree of ambiguity during decision-making by using concepts of belief and plausibility functions to general utility intervals [80].
3. **Handling absent or incomplete evaluation of an attribute:** ER can deal with all sorts of uncertainties [75] throughout the decision-making process. If there is none or incomplete data available to assess an attribute of an

alternative, the belief degrees will take that into account and enable the ER method to function normally.

4. **Handling stochastic attributes:** Usually, in complex decision-making, some attributes are stochastic in nature and are best described by a probability distribution. In such a case, the distribution will be transformed into degrees of belief, enabling the ER method to function normally.

Another feature that gives the ER approach an upper hand over the conventional MCDA methods is how it describes the MCDM problem through an extended decision matrix instead of the traditional simple decision matrix [79]. In fact, a conventional decision matrix often used for modeling an MCDA problem is only a special case of belief decision matrix used to represent the decision-making problem in the ER approach [79]. Through this matrix, each attribute of a single alternative is described by a distributed assessment using a belief structure that better incorporates degrees of uncertainty, randomness, and ignorance [79]. The major advantage of this distributed assessment is that it can model accurate and precise data while also capturing various types of uncertainties, such as probabilities and vagueness in subjective judgments. Furthermore, with the ER approach, the data does not need to be aggregated beforehand, and the model can work with the raw data as it is [79].

Considering the above points, it can be safely concluded that given the uncertainty and the hybrid nature of the problem in the context of this research, the ER approach is the most appropriate method to model strategic decision-making for the smart campus problem.

The decision problem is formalized in the next section, and the steps for applying the ER approach to the smart campus problem are laid out.

3.4. Mathematical Formulation

This praxis used the Evidential Reasoning (ER) [76],[77] approach to develop the basic decision support framework. The ER approach is one of the most popular approaches for solving MCDM problems. It was first created in 1994 and then enhanced in 2002 with weight normalization and probability assignment [74]. The ER technique combines input information and infers evidence for an alternative using the Dempster-Shafer (DS) hypothesis [73].

The ER method can deal with any uncertainty [75], [81]–[83] that arises during the decision-making stage. It uses various mathematical principles to represent any decision problem in a structured form and provide the optimal solution. Set theory expresses the analysis problem and its conceptual knowledge architecture in the framework. In contrast, probability theory is used to generate the domain knowledge and the input acquisition structure. The inference engine of the ER approach is constructed using the DS theory.

Let's consider a multi-criteria decision problem with L basic attributes under a general attribute y, where y is an abstract and complex property of an alternative that is difficult to measure directly, such as the *overall utility* of a given smart campus application. Although the general attribute cannot be measured directly, it can be estimated by measuring several more operational indicators, which are the basic attributes. In this work, the basic attributes are the critical success factors deduced earlier in 2.1.4: Implementation Cost, Operation Cost, Maintenance Cost, Stakeholder's Benefit, Project Duration, and Resource Availability.

Thus, a general attribute can be decomposed into basic attributes. Furthermore, the assessments of an alternative against each basic attribute can be aggregated to yield an overall score for the alternative on the general attribute. This process (the DS Algorithm) can be repeated for each alternative, resulting in a single, overall score, consequently allowing all alternatives to be compared by a unified scale. The best alternative would be the one that scored the highest on the general attribute.

An Architectural Theory Diagram (ATD) can describe the relationship between the general and basic attributes with a two-layer hierarchy as in Figure 2.

3.4.1.1. Basic attributes

Mathematically, the set of basic attributes can be represented as:

$$A = \{a_1, a_2, \dots, a_i, \dots, a_L\}, \tag{1}$$

where L is the number of basic attributes, and $i = 1,2, \dots, L$.

In this work, the basic attributes to establish a smart campus can be represented as,

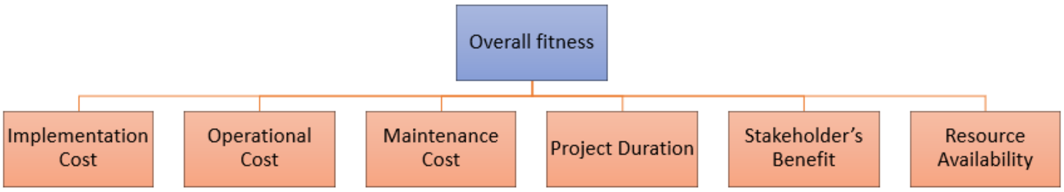

Figure 2 Decision model representation through ATD

$$\text{A} = \{\text{Implementation Cost, Operation Cost, Maintenance Cost,}$$

$$\text{Project Duration, Stakeholder's Benefit, Resource Availability}\} \tag{2}$$

Here, $L = 6$.

3.4.1.2. Evaluation grades

Consider N distinct evaluation grades for assessing an alternative's performance for a given attribute. For instance, the performance can be evaluated with three grades as in {Good, Average, and Poor}, so here, $N = 3$.

We define the set of evaluation grades as follows:

$$E = \{\mathrm{e}_1, e_2, \dots, e_n, \dots, e_N\} = \{High, Medium, Low\} \tag{3}$$

where N is the number of distinct evaluation grades, and $n = 1,2, \dots, N$.

In this work, the evaluation grades used are $E = \{Good,\ Average,\ Poor\}$,

3.4.1.3. User beliefs

The ER approach is a knowledge-based [76],[77] reasoning model that transforms expert knowledge into decision-making factors. The domain knowledge for developing the basic knowledge base can be extracted directly from domain experts as *degrees of belief*. A user's belief in the ER approach represents the degree to which the user is confident about a particular assertion [84]. The degree of belief is the basic input of the user in the ER approach and can take on any value between 0 and 1. For example, the stakeholder's benefit with a smart campus can be evaluated as {(Good, 0.7), (Average, 0.3), (Poor, 0.0)} which means the user is 70% sure that the stakeholder's benefit with a smart campus is Good, 30% sure the benefit is Average and 0% sure that benefit is Poor. Mathematically, the user's belief in the ER technique can be denoted by $\beta_{i,n}$, denoting the degree of belief for the basic attribute a_i at the evaluation grade e_n. It is the expert's degree of confidence in how well an alternative fulfills the evaluation grade e_n of a certain attribute a_i.

Like relative weights, a degree of belief is a number between 0 and 1, inclusive. However, the sum of degrees of belief for an attribute across evaluation grades need not add up to 1 if there is uncertainty in assessment, according to (4).

$$0 \leq \sum_{n=1}^{N} \beta_{i,n} \leq 1 \ \forall \, i \tag{4}$$

A *complete assessment of an attribute* implies that $\sum_{n=1}^{N} \beta_{i,n} = 1$, while an *incomplete assessment of an attribute* implies that $\sum_{n=1}^{N} \beta_{i,n} < 1$.

The decision problem in a real-life scenario normally suffers from imprecise or incomplete information, which generates uncertainty. Uncertainty due to an incomplete degree of belief [74], [76]–[78] is an uncertainty that is detected when $\sum_{n=1}^{N} \beta_{i,n} < 1$ for any i. For instance, to choose the optimal alternative to set up a smart campus, a user can provide inputs for the attribute "Stakeholder's benefit" for an alternative, say, "Smart Transportation System" as, {(Good, 0.5), (Average, 0.3), (Poor, 0.0)}. The inputs provided imply that the user is 50% confident that the stakeholder's benefit of the "Smart Transportation System" is Good, 30% confident that the stakeholder's benefit is Average, and 100% sure that the benefit is not Poor. However, the system received only an 80% confidence degree from the user, which leaves 20% uncertainty in the decision-making system.

3.4.1.4. Attribute weights

All the attributes in a decision-making process may not be equally important. So, each attribute needs to be assigned a weight. The weight of an attribute is a value [77] that ranks this attribute among other attributes based on its relative importance in the context of the decision problem.

The weights of the attributes of the decision problem can be elicited from the domain expert or be interpreted from historical data. In the ER approach, every basic attribute a_i is weighted with a numeric value, ω_i to express its relative importance in the decision-making process [77]. The weights must add up to 1 across the basic attributes, as per (5).

$$\sum_{i=1}^{L} \omega_i = 1 \tag{5}$$

Therefore, the weight of any basic attribute must be between 0 and 1, inclusive, where $0 \leq \omega_i \leq 1 \quad \forall\, i$.

3.4.1.5. Utilities

The ER approach uses the utility function to determine the desirability of an alternative. The utility of an evaluation grade e_n is denoted by u_n, where the highest possible utility value of 1 should be assigned to the most desirable evaluation grade, and the lowest possible utility value of 0 should be assigned to the least desirable evaluation grade.

For this praxis, we define u_n as per (6), where u_1 corresponds to the utility of the evaluation grade "Good", u_2 corresponds to an "Average" grade, and u_3 corresponds to a "Poor" grade.

$$\begin{aligned} u_1 &\coloneqq 1 \\ u_2 &\coloneqq 0.5 \\ u_3 &\coloneqq 0 \end{aligned} \tag{6}$$

3.4.1.6. Probability masses

If a degree of belief $\beta_{i,n}$ can be thought of as a score, then its product with the attribute weight would yield a weighted score. That is the definition of the probability mass of a basic attribute a_i at evaluation grade e_n, which is denoted by $m_{i,n}$. It represents how well a_i supports the claim that the assessment of y is e_n.

$$m_{i,n} = \omega_i \cdot \beta_{i,n} \tag{7}$$

The sum of probability masses for an attribute a_i over all evaluation grades may not add up to 1 due to uncertainty in assessment. This gives rise to a new definition: m_i^* : The remaining probability mass unassigned to attribute a_i, calculated as in equation (8).

$$m_i^* = 1 - \sum_{n=1}^{N} m_{i,n} = 1 - \omega_i \sum_{n=1}^{N} \beta_{i,n} \tag{8}$$

m_i^* can be decomposed into two components: $\bar{m}_i$ and $\tilde{m}_i$. $\bar{m}_i$ is the remaining probability mass unassigned to attribute a_i due to incomplete weight and is calculated as in equation (9), while $\tilde{m}_i$ is the remaining probability mass unassigned to attribute a_i due to incomplete degree of belief, as per equation (10).

$$\bar{m}_i = 1 - \omega_i \tag{9}$$

$$\tilde{m}_i = \omega_i \left(1 - \sum_{n=1}^{N} \beta_{i,n} \right) \tag{10}$$

3.4.1.7. Aggregated probability mass

Eventually, the overall performance of an alternative on the general attribute y can only be achieved through aggregation of the data at the basic attribute level. The aggregated measures are computed through the recursive ER algorithm for $L - 1$ iterations.

In each recursion, define the following measures aggregated across the basic attributes a_1 to a_j, where $j = \{2, \dots, L\}$:

- $M_{j,n}$ denotes the probability mass aggregated at evaluation grade e_n. It is calculated as:

$$M_{j,n} = K_j\left[M_{j-1,n} \cdot m_{j,n} + M_{j-1}^{*} \cdot m_{j,n} + M_{j-1,n} \cdot m_j^{*}\right] \tag{11}$$

- K_j is a normalization factor that ensures the aggregated probability masses remain between 0 and 1 in each recursion of the ER algorithm. It is calculated as:

$$K_j = [1 - \sum_{t=1}^{N} \sum_{\substack{k=1 \\ k \neq t}}^{N} M_{j-1,t} \cdot m_{j,k}]^{-1} \quad \forall\, j = \{2, \ldots, L\} \tag{12}$$

- M_j^{*} is the unassigned probability mass aggregated over all evaluation grades. It is the sum of $\bar{M}_j$ and $\widetilde{M}_j$.

$$M_j^{*} = \bar{M}_j + \widetilde{M}_j \tag{13}$$

- $\bar{M}_j$ is the unassigned probability mass due to incomplete weight, aggregated over all evaluation grades. It is calculated as:

$$\bar{M}_j = K_j\left[\bar{M}_{j-1} \cdot \bar{m}_j\right] \quad \forall\, j = \{2, \ldots, L\} \tag{14}$$

- $\widetilde{M}_j$ is the unassigned probability mass due to due to incomplete degrees of belief, aggregated across the basic attributes a_1 to a_j and all evaluation grades. It is calculated as:

$$\widetilde{M}_j = K_j\left[\widetilde{M}_{j-1} \cdot \widetilde{m}_j + \bar{M}_{j-1} \cdot \widetilde{m}_j + \widetilde{M}_{j-1} \cdot \bar{m}_j\right] \forall\, j = \{2, \ldots, L\} \tag{15}$$

where:

$$M_{1,n} = m_{1,n} \tag{16}$$

$$\bar{M}_1 = \bar{m}_1 \tag{17}$$

$$\widetilde{M}_1 = \widetilde{m}_1 \tag{18}$$

3.4.1.8. Aggregated degrees of belief

Once the aggregated probability masses $M_{L,n}$, $\overline{M}_L$, and $\widetilde{M}_L$ have been calculated through the recursive ER algorithm, the aggregated degrees of belief can be calculated, where B_n is the aggregated degree of belief for the general attribute y assessed to the evaluation grade e_n, according to (19).

$$B_n = \frac{M_{L,n}}{1 - \overline{M}_L} \quad \forall\, n \tag{19}$$

whereas the unassigned, aggregated degree of belief for the general attribute y is B^*, and is calculated as per (20).

$$B^* = 1 - \sum_{n=1}^{N} B_n = \frac{\widetilde{M}_L}{1 - \overline{M}_L} \tag{20}$$

3.4.1.9. Aggregated utility

Finally, the aggregated utility for y is denoted by U. Under a complete assessment with no assessment uncertainty, the aggregated utility is calculated as per equation (21).

$$U = \sum_{n=1}^{N} B_n\, u_n \tag{21}$$

However, if assessment uncertainty exists, i.e., there exists an unassigned belief, then a utility *interval* $[U_{\min}, U_{\max}]$ is calculated instead, where $U_{\min}$ and $U_{\max}$ are the minimum and maximum utilities of y for the considered alternative, respectively. The endpoints of the utility interval are defined in equations (22) and (23) below.

$$U_{\min} = \sum_{n=1}^{N} B_n\, u_n + B^* u_N \tag{22}$$

$$U_{\max} = \sum_{n=1}^{N} B_n\, u_n + B^* u_1 \tag{23}$$

Thus, the average aggregated utility, U_{avg}, is the midpoint of the utility interval:

$$U_{avg} = \frac{U_{\max} + U_{\min}}{2} \quad (24)$$

Repeating the above process for all alternatives results in a utility interval for each alternative. To be able to compare the alternatives, the *average* aggregated utility, U_{avg} is calculated for each alternative such that in the final analysis, the alternative with the highest U_{avg} is deemed optimal. A visual summary of the model's inputs and outputs is provided in Figure 3. In addition, a solved example of the DS algorithm is provided in Appendix A.

3.5. Input Data Acquisition

Generally, all the data required to build the proposed model were collected at different stages throughout this research, as summarized in Table 1.

Table 1 Summary of data sources and acquisition purposes

Data Acquired	**Source**	**Purpose**
Domain knowledge, including: 1. MCDA Methods 2. ER implementation techniques 3. Alternatives 4. Attributes 5. Evaluation Grades	Literature Review	Framework choice and model setup
Opinions about the relative importance of the smart campus alternatives	56 stakeholders, consisting of current students, alumni, and staff	Verify that the alternatives collected from the literature belong to distinct, non-overlapping categories

Attribute weights	**Group A** consisting of 9 experts, using NGT	Model setup
1. Utilities for each alternative based on the beliefs tensors provided 2. Optimal alternative based on the beliefs tensors provided	**Group B** consisting of 5 external domain experts, each prompted for utilities and optimal alternatives under 10 different decision-making situations	Model validation

According to the table above, the domain knowledge for the ER approach was acquired from the literature review. The domain knowledge involves both decision attributes and alternatives. The system used six critical decision factors to select the best option from nine alternatives.

During the model setup, the decision attributes were represented using a two-level Architectural Theory Diagram (ATD). The top of the structure represented the utility of the system, whereas the root level attributes assessed user belief for three evaluation grades.

Now that the model has been formulated in 3.4, it requires two types of inputs to run: A vector of weight attributes and a beliefs tensor, as illustrated in Figure 3.

The attribute weights of the decision model were collected using Nominal Group Technique (NGT). The NGT method involved 9 domain experts (hereinafter referred to as Group A) formed of campus staff, faculty department leads, and some operations managers, who assigned weights to the decision parameters. The experts first assigned weights to the attributes individually and then had a group discussion to finalize their voted weights individually.

The beliefs tensors for model validation were randomly generated and then provided to 5 decision-making experts external to AUS who had over 7 years of experience in decision-making tasks (hereinafter referred to as Group B). Each expert in Group B was provided with 10 decision-making scenarios represented by 10 beliefs tensors.

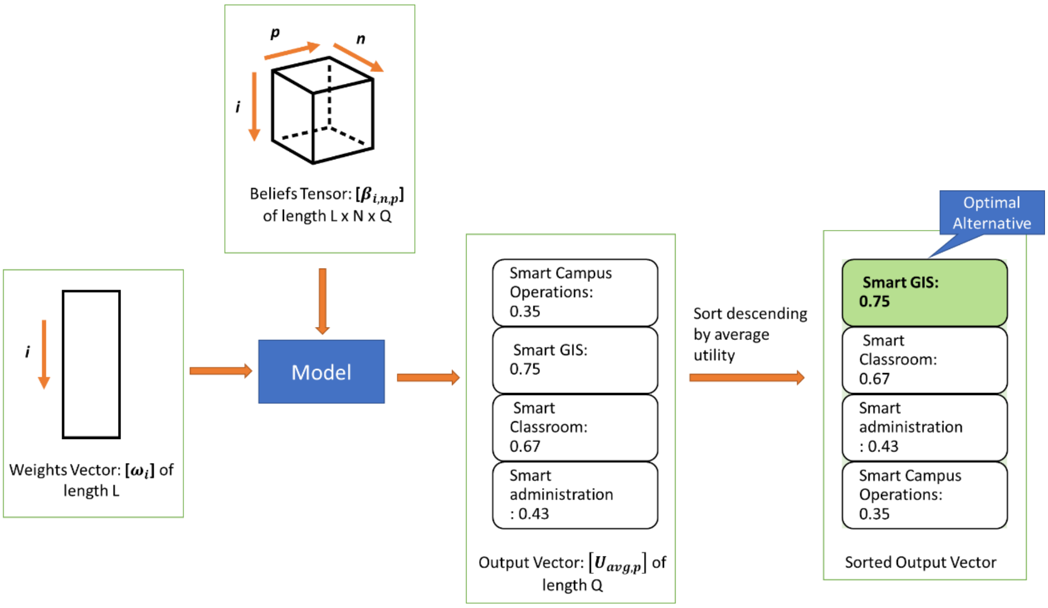

Figure 3 Visual summary of the model inputs and outputs

Each tensor was three-dimensional, consisting of 162 degrees of belief, since each run of the model requires a degree of belief to be reported at the intersection of the 6 attributes, 9 alternatives, and 3 evaluation grades. Since it would be overwhelming to prompt a human expert for 10×162 or 1,620 degrees of belief, all 1,620 elements were randomly generated and provided as-is to the experts, who were then asked to transform the given beliefs to utilities using their own experience and judgment. Consequently, 10×5 or 50 sets of inputs and expert-provided outputs were available to validate the proposed decision-making model. Therefore, the decision support model was run 50 times, and the system-generated utilities and choices of the optimal alternative were compared to utilities and optimal choices obtained through expert judgment.

The following section reports the weight figures acquired from Group A experts through the NGT. In contrast, section 3.5.2 reports the utilities and recommendations provided by Group B experts, which shall be used for validating the model in the next chapter.

3.5.1. Attribute weights

The attributes of an MCDM problem typically vary in importance and priority. Therefore, the decision attributes should be weighted based on their relative importance, which calls for a weight allocation logic. Some weight allocation techniques have already been touched on, namely, SMART and AHP. However, there are many more, such as swing weighting [85], the measuring of attractiveness by a categorically-based evaluation technique (MACBETH) [71], [86] the discrete choice experiments (DCE) [87], [88] the Potentially all pairwise rankings of all possible alternatives (PAPRIKA) methodology [89], and the conjoint analysis (CA) [90]. However, these techniques analyze historical data to derive weights for the decision attributes. Since the context of the decision problem presented in this praxis is new, no historical data is available for this problem to the author's knowledge at the time of writing. Therefore, the weights for the decision-making framework presented in this praxis were collected through a consensus method. Two popular consensus methods are the Delphi and the Nominal Group Technique (NGT) [91]. Both methods require a group of domain experts to generate their ideas for evaluating and prioritizing the decision attributes.

The NGT method relies on the moderators who arrange the group brainstorming session, whereas the Delphi method relies on the questionnaires used in the weight collection process. Therefore, through the NGT method, the moderators have a better opportunity to explain the problem clearly to the experts. On the other hand, in the Delphi method, the experts must study the problem in solitude and then make their decision, which sometimes misguides some of the experts into allocating inappropriate weights to attributes. Besides, the Delphi method requires many experts to generate ideas, whereas the NGT method can be applied to a small group of experts.

This study proposes the NGT method [92], [93] to allocate weights to decision attributes. The NGT is a structural brainstorming method that involves a group of experts engaging in discussion to agree on the relative importance of the decision attributes.

In applying the NGT for determining attribute weights, a group of experts is invited into a room. The group can be of any size. However, the facilitator must ensure that all the group members are highly experienced in the relevant domain. To initiate the NGT method, the facilitator, after gathering all participants in a room, must explain the weight allocation problems to the participants.

Each participant is given a sheet of paper to assign weights to the decision attributes. The participants are requested not to share their judgments with others. This process takes 15 to 20 minutes based on the number of attributes.

Next, each participant discloses the weights to the rest of the group members. The judgment behind the assigned weights is also provided in this stage. The facilitator notes down all the vital viewpoints. This stage normally lasts for 30 to 45 minutes.

Then, all the participants explain their understanding of each attribute and try to justify the weights they assigned. They discuss the different attributes and their importance in the decision-making process. This discussion can last for an hour or longer. In this phase, all the participants contribute in some way. Following the discussion, the participants may form new insights. Therefore, the participants are invited to revise the weights they initially assigned to each attribute if they so desire.

The facilitator finally determines the weight of each attribute through a voting process. The participants vote one by one for each attribute's weight. Finally, the weight of each attribute is determined by averaging the final weights proposed by the participants and then rounding the result to two decimal places.

In this work, a group consisting of 9 experts gave their consent to participate in a brainstorming session that best approximated the NGT method.

Each attribute in the decision support model has been assigned a specific weight based on its relative importance in the decision-making process. The attribute weights collected through the NGT are summarized in Table 2. The attribute weights are finalized by averaging the voted weights in the table above. The final weights are reported in Table 3.

Table 2 Attribute weights provided by Group A experts

General Attributes	Exp. 1	Exp. 2	Exp. 3	Exp. 4	Exp. 5	Exp. 6	Exp. 7	Exp. 8	Exp. 9
Implementation Cost	0.2	0.2	0.25	0.3	0.2	0.2	0.3	0.3	0.25
Maintenance Cost	0.15	0.10	0.2	0.1	0.10	0.15	0.1	0.1	0.1
Operation Cost	015	0.15	0.15	0.1	0.15	015	0.1	0.1	0.2
Project Duration	0.15	0.15	0.1	0.1	0.15	0.15	0.1	0.1	0.1
Stakeholder's Benefit	0.2	0.25	0.2	0.3	0.25	0.2	0.3	0.3	0.25
Resource Availability	0.15	0.15	0.1	0.1	0.15	0.15	0.1	0.1	0.1

3.5.2. Degrees of belief

A single run of the model requires a three-dimensional, 162-element beliefs tensor consisting of a degree of belief at each intersection of each evaluation grade, attribute, and alternative, which should be provided by the user. The proposed system considers three grades for evaluating each attribute, as in Table 4.

A beliefs tensor can be captured using a spreadsheet file that resembles Table 5, in which a user would provide a degree of belief against three evaluation grades for each of the six attributes and nine alternatives on a scale of 0 to 1, which determines the confidence level from 0 to 100%. To validate the system output, utilities were elicited from 5 decision-making experts for 50 randomly generated beliefs tensors. Corresponding to each beliefs tensor, each expert was also asked to select the best alternative, typically the one which was assigned the maximum utility. The utilities provided by the experts and the corresponding optimal alternatives are reported in Table 6.

With all the building blocks and inputs of the ER framework fully defined, we are ready to implement the ER model in a programming environment. The following section discusses the model implementation steps and the software architecture.

Table 3 Final attribute weights

General Attribute	**Weight**
Implementation Cost	0.20
Maintenance Cost	0.10
Operation Cost	0.15
Project Duration	0.15
Stakeholder's Benefit	0.25
Resource Availability	0.15

Table 4 Evaluation grades for each attribute

General Attributes	**Evaluation Grades**
Development Cost	Low (Good), Medium (Average), High (Poor)
Maintenance Cost	Low (Good), Medium (Average), High (Poor)
Operation Cost	Low (Good), Medium (Average), High (Poor)
Implementation Duration	Short (Good), Medium (Average), Long (Poor)
Stakeholder's Benefit	High (Good), Medium (Average), Low (Poor)
Resource Availability	Yes (Good), Not Sure (Average), No (Poor)

Table 5 Example data entry form to elicit elements of the beliefs tensor

Attribute	Evaluation Grade	Alternatives								
		A1	A2	A3	A4	A5	A6	A7	A8	A9
Implementation Cost	Good	0	0.5	0	0.3	0.9	0.7	0.1	0.6	0.4
	Average	0.5	0.5	0.5	0.3	0.05	0.3	0.2	0.3	0.6
	Poor	0.5	0	0.5	0.4	0.05	0	0.7	0.1	0
Operation Cost	Good	0.6	0.6	0.6	0.1	0.6	0.4	0.3	0.9	0.7
	Average	0.3	0.3	0.3	0.2	0.3	0.6	0.3	0.05	0.3
	Poor	0.1	0.1	0.1	0.7	0.1	0	0.4	0.05	0
Maintenance Cost	Good	0.1	0.6	0.4	0.3	0.9	0.7	0	0.5	0
	Average	0.2	0.3	0.6	0.3	0.05	0.3	0.5	0.5	0.5
	Poor	0.7	0.1	0	0.4	0.05	0	0.5	0	0.5
Stakeholder's Benefit	Good	0	0.5	0	0.1	0.6	0.4	0.6	0.6	0.6
	Average	0.5	0.5	0.5	0.2	0.3	0.6	0.3	0.3	0.3
	Poor	0.5	0	0.5	0.7	0.1	0	0.1	0.1	0.1
Implementation Duration	Good	0.6	0.6	0.6	0	0.5	0	0.1	0.6	0.4
	Average	0.3	0.3	0.3	0.5	0.5	0.5	0.2	0.3	0.6
	Poor	0.1	0.1	0.1	0.5	0	0.5	0.7	0.1	0
Resource Availability	Good	0.4	0.25	0.4	0.1	0.6	0.4	0	0.5	0
	Average	0.6	0.25	0.6	0.2	0.3	0.6	0.5	0.5	0.5
	Poor	0	0.5	0	0.7	0.1	0	0.5	0	0.5

Table 6 Expert-provided utilities per alternative

No.	Utilities									Optimal Alternative
	A1	A2	A3	A4	A5	A6	A7	A8	A9	
1	1	0	0	0	0	0	0	0	0	A1
2	0	1	0	0	0	0	0	0	0	A2
3	0	0	1	0	0	0	0	0	0	A3
4	0	0	0	1	0	0	0	0	0	A4
5	0	0	0	0	1	0	0	0	0	A5
6	0	0	0	0	0	1	0	0	0	A6
7	0	0	0	0	0	0	1	0	0	A7
8	0	0	0	0	0	0	0	1	0	A8
9	0	0	0	0	0	0	0	0	1	A9
10	1	0	0	0	0	0	0	0	0	A1
11	1	0	0	0	0	0	0	0	0	A1

12	0.25	0.25	0.75	0.25	0.25	0.25	0.25	0.25	0.25	A3
13	0.25	0.25	0.25	0.75	0.25	0.25	0.25	0.25	0.25	A4
14	0.25	0.25	0.25	0.25	0.75	0.25	0.25	0.25	0.25	A5
15	0.25	0.25	0.25	0.25	0.25	0.75	0.25	0.25	0.25	A6
16	0.25	0.25	0.25	0.25	0.25	0.25	0.75	0.25	0.25	A7
17	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.75	0.25	A8
18	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.75	A9
19	0.5	0.2	0.2	0.2	0.2	0.2	0.2	0.2	0.2	A1
20	0.2	0.5	0.2	0.2	0.2	0.2	0.2	0.2	0.2	A2
21	0.2	0.2	0.5	0.2	0.2	0.2	0.2	0.2	0.2	A3
22	0.2	0.2	0.2	0.5	0.2	0.2	0.2	0.2	0.2	A4
23	0.2	0.2	0.2	0.2	0.5	0.2	0.2	0.2	0.2	A5
24	0.2	0.2	0.2	0.2	0.2	0.5	0.2	0.2	0.2	A6
25	0.2	0.2	0.2	0.2	0.5	0.2	0.5	0.2	0.2	A7
26	0.2	0.2	0.2	0.2	0.5	0.2	0.2	0.5	0.2	A8
27	0.2	0.2	0.2	0.2	0.5	0.2	0.2	0.5	0.2	A8
28	0.5	0.5	0.6	0.6	0.6	0.7	0.6	0.65	0.5	A6
29	0.59	0.67	0.45	0.49	0.49	0.6	0.58	0.58	0.7	A9
30	0.65	0.7	0.45	0.55	0.6	0.65	0.56	0.7	0.6	A2
31	0.7	0.75	0.5	0.4	0.65	0.6	0.6	0.75	0.6	A2
32	0.4	0.55	0.6	0.6	0.6	0.75	0.6	0.65	0.7	A6
33	0.6	0.6	0.6	0.72	0.55	0.65	0.7	0.15	0.7	A4
34	0.651	0.65	0.6	0.6	0.6	0.7	0.6	0.7	0.15	A6
35	0.7	0.15	0.65	0.65	0.6	0.6	0.6	0.7	0.55	A1
36	0.15	0.65	0.65	0.6	0.7	0.55	0.6	0.6	0.7	A5
37	0.15	0.65	0.7	0.6	0.7	0.55	0.6	0.6	0.7	A9
38	0.6	0.7	0.55	0.7	0.65	0.65	0.15	0.65	0.6	A2
39	0.45	0.7	0.5	0.25	0.8	0.7	0.35	0.8	0.6	A5
40	0.45	0.75	0.55	0.65	0.55	0.8	0.65	0.55	0.55	A6
41	0.75	0.5	0.8	0.7	0.6	0.78	0.75	0.5	0.7	A3
42	0.6	0.3	0.6	0.6	0.5	0.6	0.3	0.75	0.4	A8
43	0.65	0.55	0.8	0.7	0.5	0.7	0.45	0.6	0.7	A3
44	0.3	0.6	0.7	0.5	0.8	0.65	0.3	0.5	0.65	A5
45	0.3	0.45	0.55	0.3	0.6	0.5	0.2	0.8	0.45	A8
46	0.65	0.65	0.8	0.7	0.55	0.85	0.55	0.55	0.7	A6
47	0.6	0.15	0.45	0.4	0.3	0.45	0.3	0.6	0.45	A8
48	0.5	0.45	0.5	0.4	0.4	0.7	0.5	0.65	0.35	A6
49	0.4	0.35	0.45	0.4	0.45	0.45	0.4	0.55	0.35	A8
50	0.65	0.4	0.6	0.35	0.5	0.45	0.35	0.45	0.45	A1

3.6. Decision Support System Implementation

Implementing the decision support tool involves the construction of a knowledge capture matrix and knowledge manipulation algorithms. The basic knowledge capture matrix in this system was developed through the literature review, while the domain experts provided the attribute weights. The knowledge manipulation (otherwise known as the aggregation engine) was developed following the DS algorithm.

3.6.1. Implementation technology

The proposed decision support system was developed with Python (3.9 version). In addition, the PyCharm Community Edition 2022.3.2 was used as the Integrated Development Environment (IDE). A snapshot of the IDE is in Figure 4.

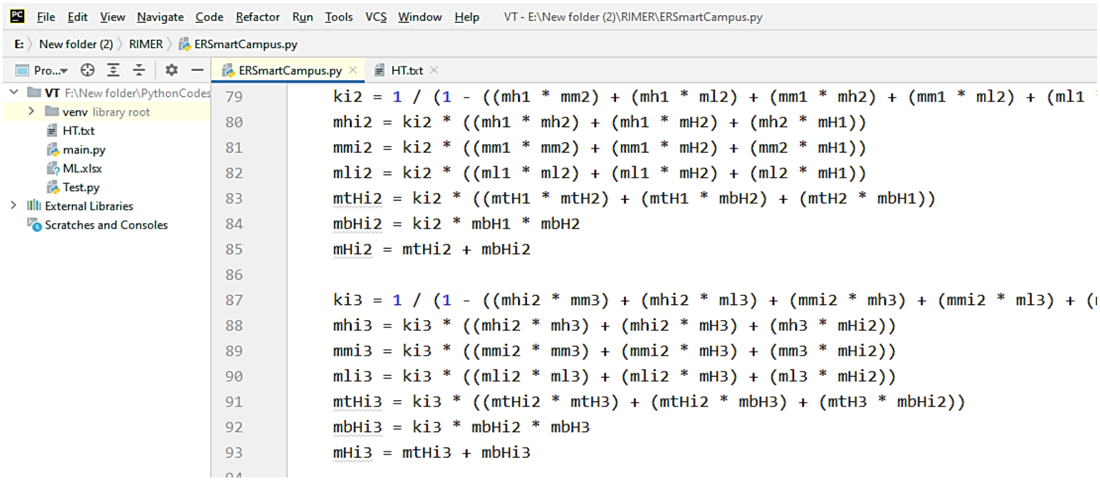

Figure 4 System development in Python

3.6.2. System architecture

The architecture of the decision support tool at the three structural layers: Presentation, Application, and Data Processing Layers [94] is illustrated in Figure 5.

The presentation layer in the above structural diagram represents the system's interface. The system interface receives inputs from the users and provides the outputs to the users. The application layer performs all sorts of mathematical operations. It interacts with both the presentation and data management layers to deduce the modular efficiency. The data processing layer consists of fundamental knowledge resources.

The inference engine in the proposed decision support system was developed using the DS theory**.** The DS theory recursively combines the probability masses and beliefs of the basic attributes. The combined probability masses in the ER approach are normalized and used to produce the utilities of decision alternatives. The logic of the inference engine is illustrated by the flowchart in Figure 6.

In the next chapter, the model's inputs and outputs are validated and its performance is assessed.

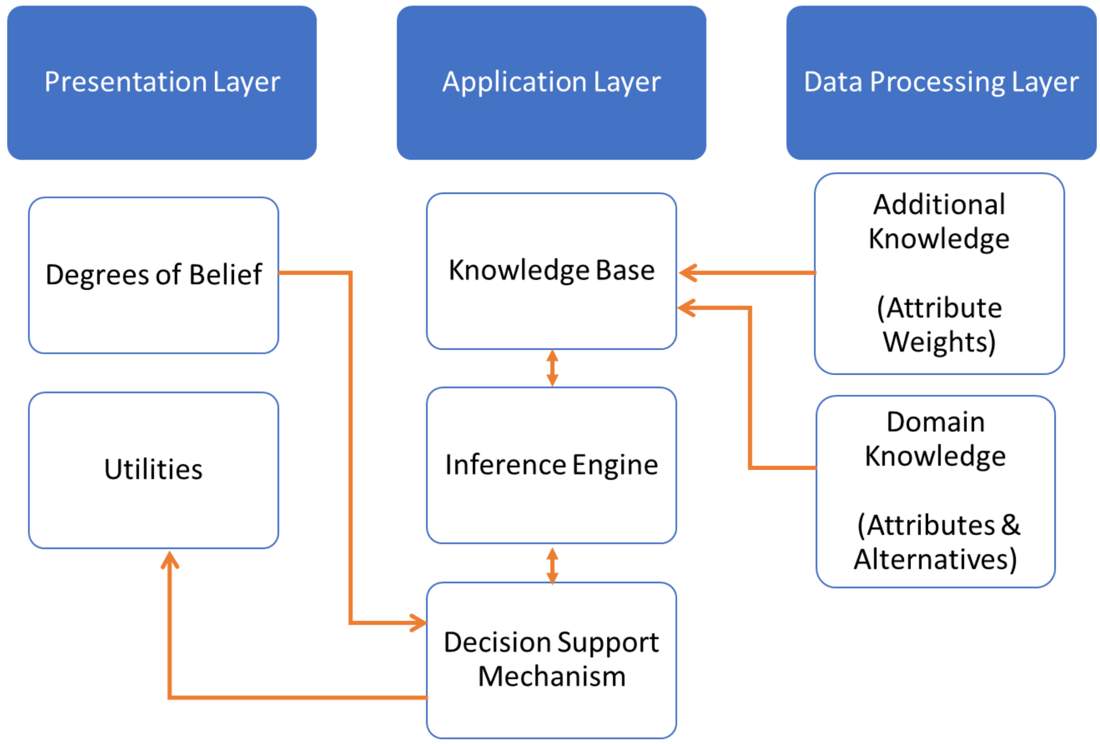

Figure 5 Structural design of the system components

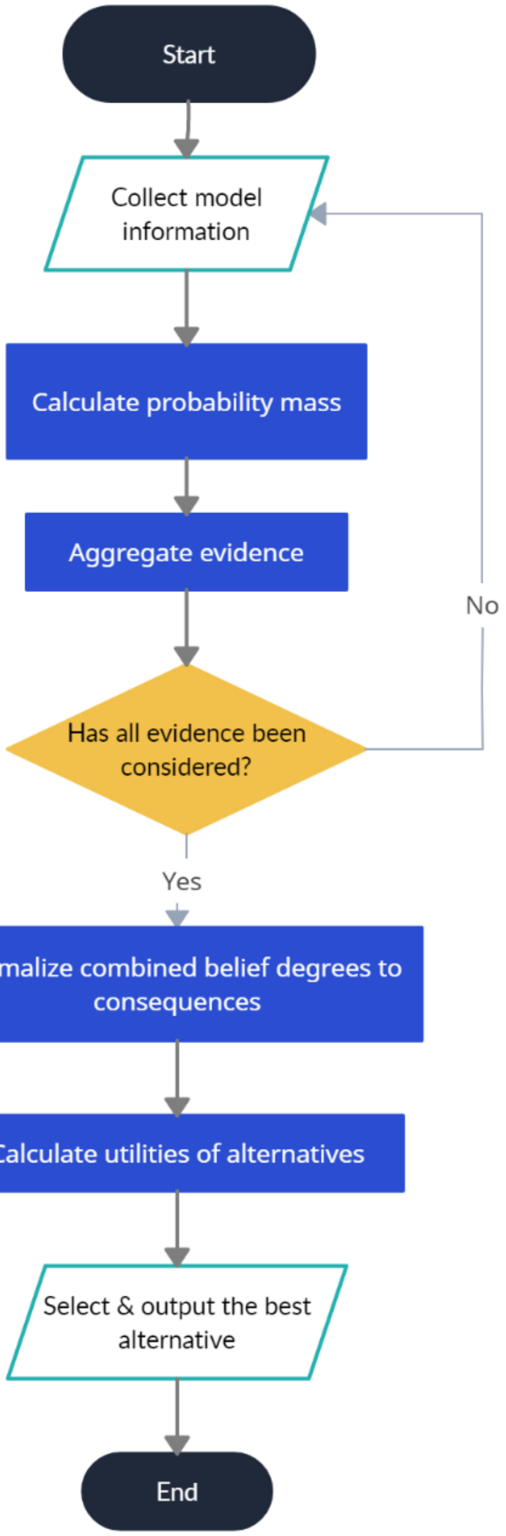

Figure 6 Inference engine flowchart

3.1. Conclusion

This chapter laid out in detail the research methodology followed in this work, followed by a critical review of families of decision-making methodologies. MCDM methods were deemed the most suitable for decision-making at the strategic level. Furthermore, the Evidential Reasoning (ER) approach in particular, came out as the best-suited decision-making framework for the smart campus problem. In consequence, The Evidential Reasoning (ER) framework was formulated mathematically based on the Dempster-Shafer (DS) algorithm. Yet, another building block of the ER framework had to be defined: The attribute weights.

The Nominal Group Technique (NGT) was used to develop the basic knowledge base of the proposed decision-making engine. Figure 7 illustrates how the ER technique follows from the output of the NGT.

Lastly, this chapter described how the model was developed in Python for this study. The results provided by this prototype will be tested and analyzed in the next chapter.

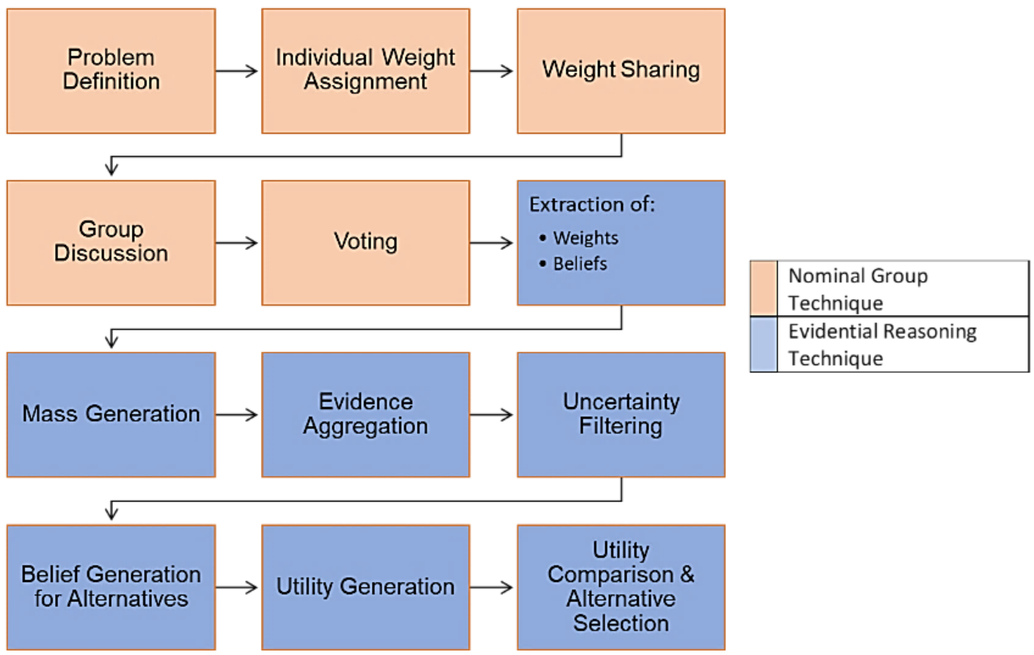

Figure 7 Diagram illustrating the interaction between NGT and ER

Chapter 4. Results and Validation

The chapter begins with validating two important building blocks of the model: The alternatives and the attribute weights. The alternatives shall be validated through a stakeholder opinion survey conducted at AUS. In contrast, an attempt to validate the attribute weights has been performed by assessing the model's sensitivity to weight perturbations.

Secondly, the chapter also demonstrates sample outputs from the model implementation in Python.

Lastly, model validation was carried out by applying statistical tests and computing several other performance measures, such as the confusion matrix, Receiver Operating Characteristic (ROC) curve, accuracy, specificity, precision, and F1-score, among others.

4.1. Validation of Model Constituents

4.1.1. Validation of alternatives

A survey was conducted on 56 stakeholders to validate the nine functional families of smart campus applications deduced from the literature survey in 2.1.3. The sample successfully captured the responses of representatives of three types of vital stakeholders: Students, alumni, and staff, who are not considered smart campus experts. The respondents rated the importance of various smart campus applications on a scale from 0 to 5, with 5 being the highest preference and 0 being the least. Table 7 reports the full survey data. Summary statistics of the survey data are reported in Table 8.

Table 7 Full data for stakeholder's opinion survey

Stakeholder #	Role	A.1. Smart Learning Management System	A.2. Smart Campus Operations	A.3. Safe Learning Environment	A.4. Smart Geographic Information System	A.5. Smart Administrative System	A.6. Waste & Water Management System	A.7. Sustainable Energy Management System	A.8. Smart Classrooms	A.9. Smart Transportation System	Which, in your opinion, is a must-have System at your University?
1	Alumni	4	5	3	4	5	4	3	3	3	A5
2	Alumni	5	4	4	3	5	3	4	3	4	A1

3	Alumni	5	5	4	3	4	5	4	4	4	A1
4	Alumni	5	5	5	4	5	4	5	4	4	A2
5	Alumni	3	4	5	3	2	5	5	4	4	A7
6	Alumni	5	4	4	5	4	5	5	5	5	A1
7	Alumni	4	5	4	5	4	5	5	4	3	A4
8	Alumni	5	5	5	5	5	5	4	2	5	A1
9	Alumni	4	5	2	5	4	2	2	4	5	A9
10	Alumni	4	4	3	5	5	4	5	3	5	A7
11	Alumni	5	5	5	5	5	3	5	5	5	A9
12	Alumni	4	4	5	4	3	3	4	4	5	A3
13	Alumni	5	4	4	2	3	4	5	4	4	A1
14	Alumni	5	5	4	5	5	4	3	2	5	A5
15	Alumni	5	5	5	4	5	5	5	4	5	A3
16	Alumni	5	5	5	5	5	5	5	4	4	A1
17	Alumni	5	4	4	3	4	4	5	3	3	A1
18	Alumni	4	4	2	4	5	5	5	3	2	A5
19	Alumni	5	4	5	4	5	5	5	5	5	A8
20	Alumni	5	5	5	5	4	5	5	5	5	A1
21	Alumni	5	5	4	2	4	4	5	3	5	A9
22	Alumni	4	4	5	3	3	4	5	4	3	A7
23	Alumni	4	5	5	4	4	5	5	4	4	A8
24	Alumni	5	5	5	5	5	4	4	5	5	A4
25	Alumni	3	5	2	4	4	4	4	2	4	A2
26	Alumni	4	4	5	4	4	5	3	4	3	A1
27	Alumni	4	5	5	5	5	5	5	3	3	A5
28	Alumni	4	4	3	4	5	4	5	5	5	A5
29	Alumni	4	3	1	4	5	5	4	4	3	A6
30	Staff	3	4	2	2	4	4	2	2	4	A4
31	Student	4	4	2	3	4	4	4	3	2	A2
32	Student	5	5	5	5	5	5	5	5	5	A4
33	Student	3	5	4	5	5	5	5	5	5	A4
34	Student	5	4	5	3	4	3	3	4	4	A1
35	Student	5	5	5	3	4	5	3	4	5	A3
36	Student	4	5	5	4	5	5	5	3	3	A7
37	Student	4	5	5	4	5	5	5	5	4	A5
38	Student	5	5	5	3	5	5	5	3	4	A3
39	Student	4	4	4	4	4	5	5	5	4	A3
40	Student	4	5	4	5	5	4	5	5	5	A8
41	Student	4	4	3	4	3	4	3	4	4	A1
42	Student	5	5	5	5	5	5	5	5	5	A1
43	Student	5	4	5	5	5	3	4	2	3	A1

44	Student	3	4	5	5	5	5	5	4	5	A4
45	Student	3	4	3	2	3	3	3	3	3	A4
46	Student	4	4	3	5	5	5	5	2	5	A3
47	Student	3	5	3	1	5	5	4	5	3	A5
48	Student	4	4	5	4	4	5	5	4	4	A4
49	Student	5	5	5	5	5	5	5	5	5	A1
50	Student	5	4	3	3	4	3	4	5	5	A1
51	Student	3	5	5	4	5	5	2	3	4	A2
52	Student	4	4	4	4	4	4	4	4	4	A1
53	Student	5	5	5	3	4	5	5	4	5	A9
54	Student	4	5	3	2	5	4	5	4	5	A2
55	Student	5	4	4	5	4	2	4	5	5	A1
56	Student	5	4	5	3	3	5	5	3	5	A1

Table 8 Data summary for the stakeholders' opinion survey

Groups	*Count*	*Sum*	*Average*	*Variance*
A.1. Smart Learning Management System	56	242	4.321428571	0.512987013
A.2. Smart Campus Operations	56	252	4.5	0.290909091
A.3. Safe Learning Environment	56	230	4.107142857	1.188311688
A.4. Smart Geographic Information System	56	219	3.910714286	1.100974026
A.5. Smart Administrative System	56	245	4.375	0.565909091
A.6. Waste & Water Management System	56	243	4.339285714	0.700974026
A.7. Sustainable Energy Management System	56	244	4.357142857	0.815584416
A.8. Smart Classrooms	56	215	3.839285714	0.937337662
A.9. Smart Transportation System	56	235	4.196428571	0.778896104

A single-factor, two-way ANOVA test was performed on the stakeholders' opinion data to ascertain whether the proposed smart campus alternatives represent distinct, non-overlapping categories. The ANOVA test (reported in Table 9) yielded a p-value of 0.000379, which is less than 0.05. Therefore, the difference in stakeholder preference between the nine different decision alternatives is statistically significant.

Table 9 Results of the single-factor, two-way ANOVA test on stakeholder survey data

SUMMARY				
Groups	*Count*	*Sum*	*Average*	*Variance*
A.1. Smart Learning Management System	56	242	4.321	0.513
A.2. Smart Campus Operations	56	252	4.500	0.291
A.3. Safe Learning Environment	56	230	4.107	1.188
A.4. Smart Geographic Information System	56	219	3.911	1.101
A.5. Smart Administrative System	56	245	4.375	0.566
A.6. Waste & Water Management System	56	243	4.339	0.701
A.7. Sustainable Energy Management System	56	244	4.357	0.816
A.8. Smart Classrooms	56	215	3.839	0.937
A.9. Smart Transportation System	56	235	4.196	0.779

ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	22.37	8.00	2.7966	3.6521	0.0004	1.9571
Within Groups	379.05	495.00	0.7658			
Total	401.43	503.00				

4.1.2. Validation of attribute weights

The attribute weights used for this praxis were collected using the NGT. In general, varying the weights is expected to change the optimal alternative recommended by the system, and even more so as the larger weights are perturbed since the model would be more sensitive to the 'heavier' attributes. If initially, the model perfectly emulated an expert under the original set of weights, then one way to validate the attribute weights would be to measure how stable the model's recommendations remain if the weights were to fluctuate slightly from their original values. We posit that if the model's recommendation deviates from the ideal due to a slight fluctuation in an attribute's weight by a larger degree than what the magnitude of the weight should warrant, then that should call into question the reliability of the said weight.

Five out of 50 randomly generated beliefs tensors were selected, such that their corresponding outputs from the model are identical to the expert-recommended alternative under the original set of weights. Afterward, the attribute weights were adjusted one at a time. Each time, the weight of an attribute would be increased or decreased by a certain proportion, and the other weights would be adjusted accordingly, such that all the weights add up to 1.

Each weight was changed by 25% and 50% in either direction, one at a time, creating 4 new sets of weights per attribute, as shown in Table 10. Hence, the model was re-run 24 times (=6 attributes × 4 weight sets) for each of the five beliefs tensors, or 24×5 = 120 times in total. The resulting optimal alternative and its utility were recorded after each run. Only the utilities of the optimal alternatives (given in

Several pooled confusion matrices [95], [96] were developed. Based on the confusion matrices, the performance of the system in terms of accuracy, sensitivity, specificity, etc., was reported for each set of weights. Table 13 shows how the weights of attributes affect the system's performance.

The variation in system performance due to the weight change can be visualized more transparently using the bar chart in Figure 8.

Figure 8 shows the model is sensitive to the attributes' weights. The model's accuracy fluctuates due to changes in the attribute weights, as it should. It also shows that the weights allocated by experts ensure the 100% accuracy of the system. Thus, the weights collected through the NGT method confirm its validity.

Table 11) were used to compare against the expert-provided utilities. Furthermore, a comparison of the system's decision accuracy against the truth data was performed and reported in Table 12.

Table 10 Attribute weight variation

Attributes	***Attribute being controlled***	***Actual Weight***	***Weight decreased by 25%***	***Weight decreased by 50%***	***Weight increased by 25%***	***Weight increased by 50%***
		Set 1	***Set 2***	***Set 3***	***Set 4***	***Set 5***
Implementation Cost	✓	**0.2**	**0.15**	**0.1**	**0.25**	**0.3**
Operation Cost		0.15	0.16	0.17	0.14	0.13
Maintenance Cost		0.1	0.11	0.12	0.09	0.08
Stakeholders' Benefit		0.25	0.26	0.27	0.24	0.23
Implementation Duration		0.15	0.16	0.17	0.14	0.13

Resource Availability		0.15	0.16	0.17	0.14	0.13
Implementation Cost		0.2	0.2075	0.215	0.1925	0.185
Operation Cost	✓	**0.15**	**0.1125**	**0.075**	**0.1875**	**0.225**
Maintenance Cost		0.1	0.1075	0.115	0.0925	0.085
Stakeholders' Benefit		0.25	0.2575	0.265	0.2425	0.235
Implementation Duration		0.15	0.1575	0.165	0.1425	0.135
Resource Availability		0.15	0.1575	0.165	0.1425	0.135
Implementation Cost		0.2	0.205	0.21	0.195	0.19
Operation Cost		0.15	0.155	0.16	0.145	0.14
Maintenance Cost	✓	**0.1**	**0.075**	**0.05**	**0.125**	**0.15**
Stakeholders' Benefit		0.25	0.255	0.26	0.245	0.24
Implementation Duration		0.15	0.155	0.16	0.145	0.14
Resource Availability		0.15	0.155	0.16	0.145	0.14
Implementation Cost		0.2	0.2152	0.225	0.1875	0.175
Operation Cost		0.15	0.1625	0.175	0.1375	0.125
Maintenance Cost		0.1	0.1125	0.125	0.0875	0.075
Stakeholders' Benefit	✓	**0.25**	**0.1875**	**0.125**	**0.3125**	**0.375**
Implementation Duration		0.15	0.1625	0.175	0.1325	0.125
Resource Availability		0.15	0.1625	0.175	0.1375	0.125
Implementation Cost		0.2	0.2075	0.215	0.1925	0.185
Operation Cost		0.15	0.1125	0.075	0.1875	0.225
Maintenance Cost		0.1	0.1075	0.115	0.0925	0.085
Stakeholders' Benefit		0.25	0.2575	0.265	0.2425	0.235
Implementation Duration	✓	**0.15**	**0.1575**	**0.165**	**0.1425**	**0.135**
Resource Availability		0.15	0.1575	0.165	0.1425	0.135
Implementation Cost		0.2	0.2075	0.215	0.1925	0.185
Operation Cost		0.15	0.1125	0.075	0.1875	0.225
Maintenance Cost		0.1	0.1075	0.115	0.0925	0.085
Stakeholders' Benefit		0.25	0.2575	0.265	0.2425	0.235
Implementation Duration		0.15	0.1575	0.165	0.1425	0.135
Resource Availability	✓	**0.15**	**0.1575**	**0.165**	**0.1425**	**0.135**

Several pooled confusion matrices [95], [96] were developed. Based on the confusion matrices, the performance of the system in terms of accuracy, sensitivity, specificity, etc., was reported for each set of weights. Table 13 shows how the weights of attributes affect the system's performance.

The variation in system performance due to the weight change can be visualized more transparently using the bar chart in Figure 8.

Figure 8 shows the model is sensitive to the attributes’ weights. The model's accuracy fluctuates due to changes in the attribute weights, as it should. It also shows that the weights allocated by experts ensure the 100% accuracy of the system. Thus, the weights collected through the NGT method confirm its validity.

Table 11 Variation in the utility of the optimal alternative due to change in weight[2]

Utilities under original weights	**Decreasing Weight by 25%**						**Decreasing Weight by 50%**						**Increasing Weight by 25%**						**Increasing Weight by 50%**					
	Implementation Cost	Operation Cost	Maintenance Cost	Stakeholder’ s Benefit	Implementation Duration	Resource Availability	Implementation Cost	Operation Cost	Maintenance Cost	Stakeholder’ s Benefit	Implementation Duration	Resource Availability	Implementation Cost	Operation Cost	Maintenance Cost	Stakeholder’ s Benefit	Implementation Duration	Resource Availability	Implementation Cost	Operation Cost	Maintenance Cost	Stakeholder’ s Benefit	Implementation Duration	Resource Availability
Beliefs Tensor 1																								
0.81	0.79	0.81	0.82	0.79	0.81	0.81	0.77	0.80	0.58	0.78	0.80	0.80	0.83	0.82	0.80	0.83	0.82	0.82	0.83	0.57	0.79	0.85	0.57	0.57
Beliefs Tensor 2																								
0.85	0.86	0.86	0.85	0.84	0.86	0.86	0.87	0.87	0.85	0.83	0.87	0.87	0.84	0.85	0.85	0.86	0.85	0.85	0.84	0.84	0.85	0.87	0.84	0.84
Beliefs Tensor 3																								
0.61	0.60	0.64	0.60	0.65	0.64	0.64	0.59	0.67	0.60	0.69	0.67	0.67	0.63	0.63	0.62	0.60	0.63	0.63	0.84	0.65	0.63	0.59	0.65	0.65
Beliefs Tensor 4																								
0.66	0.69	0.68	0.66	0.65	0.68	0.68	0.74	0.70	0.66	0.63	0.70	0.70	0.69	0.63	0.66	0.68	0.63	0.63	0.69	0.61	0.67	0.71	0.61	0.61

[2] Figures were rounded to 2 decimal places for readability

Beliefs Tensor 5																								
0.55	0.55	0.54	0.56	0.59	0.54	0.54	0.55	0.53	0.66	0.63	0.53	0.53	0.55	0.56	0.54	0.51	0.56	0.56	0.55	0.57	0.52	0.47	0.57	0.57

Table 12 Variation in the optimal alternative due to changes in weight

Actual Output	**Decreasing Weight by 25%**						**Decreasing Weight by 50%**						**Increasing Weight by 25%**						**Increasing Weight by 50%**					
	Implementation Cost	Operation Cost	Maintenance Cost	Stakeholder’ s Benefit	Implementation Duration	Resource Availability	Implementation Cost	Operation Cost	Maintenance Cost	Stakeholder’ s Benefit	Implementation Duration	Resource Availability	Implementation Cost	Operation Cost	Maintenance Cost	Stakeholders Benefit	Implementation Duration	Resource Availability	Implementation Cost	Operation Cost	Maintenance Cost	Stakeholder’ s Benefit	Implementation Duration	Resource Availability
Beliefs Tensor 1																								
A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8
Beliefs Tensor 2																								
A6	A6	A6	A6	A6	A6	A6	A6	A6	A6	A6	A6	A6	A6	A6	A6	A6	A6	A6	A6	A6	A6	A6	A6	A6
Beliefs Tensor 3																								
A1	A8	A1	A1	A8	A1	A1	A8	A1	A1	A8	A1	A1	A1	A8	A1	A1	A8	A8	A6	A8	A1	A1	A8	A8
Beliefs Tensor 4																								
A8	A6	A8	A8	A8	A8	A8	A6	A8	A8	A8	A8	A8	A8	A8	A8	A6	A8	A8	A8	A8	A8	A6	A8	A8
Beliefs Tensor 5																								
A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8	A8

Table 13 Variation in the model’s performance metrics due to change in weight

	Value under original weights	**Decreasing Weight by 25%**						**Decreasing Weight by 50%**						**Increasing Weight by 25%**						**Increasing Weight by 50%**					
		Implementation Cost	Operation Cost	Maintenance Cost	Stakeholder’ s Benefit	Implementation Duration	Resource Availability	Implementation Cost	Operation Cost	Maintenance Cost	Stakeholder’ s Benefit	Implementation Duration	Resource Availability	Implementation Cost	Operation Cost	Maintenance Cost	Stakeholder’ s Benefit	Implementation Duration	Resource Availability	Implementation Cost	Operation Cost	Maintenance Cost	Stakeholder’ s Benefit	Implementation Duration	Resource Availability
Precision	1.0	0.6	1.0	1.0	0.8	1.0	1.0	0.6	1.0	1.0	0.8	1.0	1.0	1.0	0.8	1.0	0.75	0.8	0.8	0.8	0.8	1.0	0.75	0.8	0.8

Accuracy	Specificity	Sensitivity	Negative Predicted Value
1.0	1.0	1.0	1.0
0.7	0.67	0.75	0.8
1.0	1.0	1.0	1.0
1.0	1.0	1.0	1.0
0.9	0.83	1.0	1.0
1.0	1.0	1.0	1.0
1.0	1.0	1.0	1.0
0.7	0.67	0.75	0.8
1.0	1.0	1.0	1.0
1.0	1.0	1.0	1.0
0.9	0.83	1.0	1.0
1.0	1.0	1.0	1.0
1.0	1.0	1.0	1.0
1.0	1.0	1.0	1.0
0.9	0.83	1.0	1.0
1.0	1.0	1.0	1.0
0.75	0.75	0.75	0.75
0.9	0.83	1.0	1.0
0.9	0.83	1.0	1.0
0.9	0.83	1.0	1.0
0.9	0.83	1.0	1.0
1.0	1.0	1.0	1.0
0.75	0.75	0.75	0.75
0.9	0.83	1.0	1.0
0.9	0.83	1.0	1.0

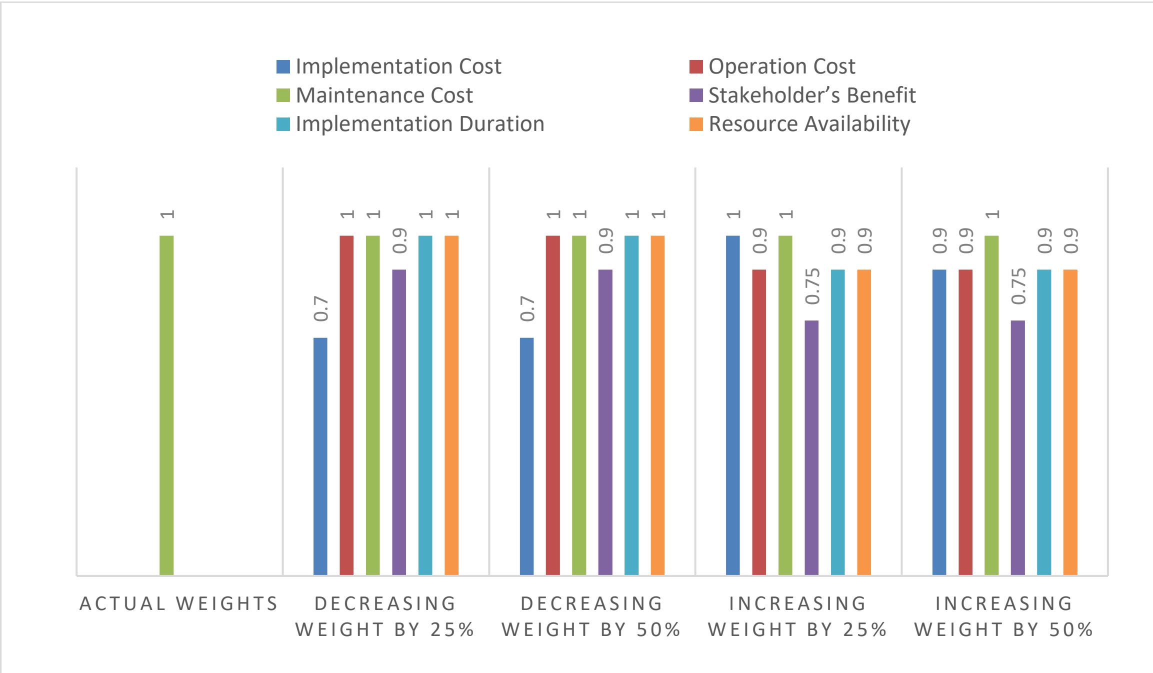

Figure 8 Bar chart of changes in accuracy due to changes in weight

Having validated the proposed alternatives and averaged NGT weights, they were programmed into the model. The model was subsequently run through 50 randomly-generated beliefs tensors that formed the validation dataset. In the next section, the various outputs for a single run of the model are demonstrated.

4.2. Model Output

The proposed model's main outputs are a vector of the average utilities, U_{avg} for each alternative. Based on that, an optimally ranked list of the alternatives in descending order of U_{avg} is also produced. If the end user desires a single recommendation, it would simply be the first alternative in the ranked list. The average utility of each alternative is demonstrated in the PyCharm console as in Figure 9.

For a better understanding of the results, the system's output is also demonstrated using a bar chart, as in Figure 10.

Figure 10 shows the utility of different alternatives. From this diagram, it becomes clear that alternative "A8" reaches the peak, and hence "A8" should be considered first to set up the smart campus.

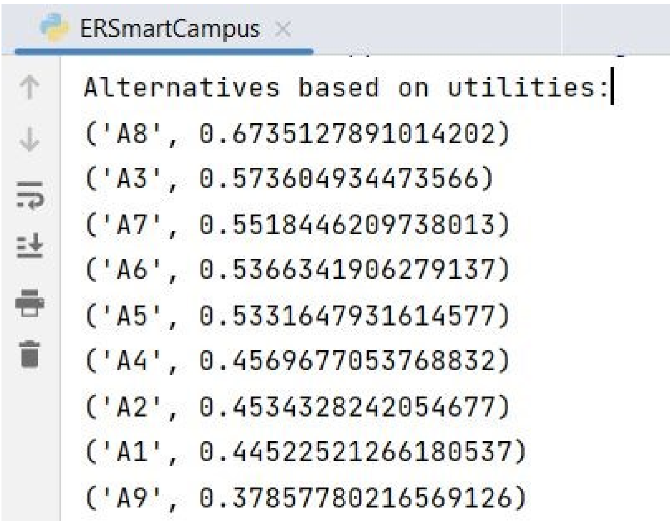

Figure 9 Example model output: Ranked list of alternatives by average utility

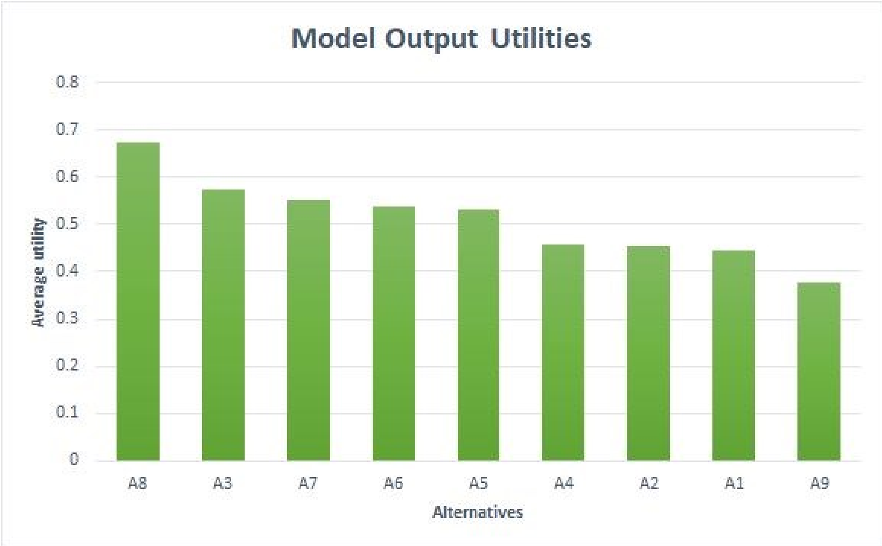

Figure 10 Example model output: Pareto chart of average utilities of alternatives

The model was also programmed to graphically report some intermediary variables, which may be useful to an expert user wishing to validate or debug the model. For example, the model outputs a bar graph of B_n (the aggregated degree of belief by evaluation grade for an alternative) as shown in Figure 11. The matplotlib (version 3.3.3) library is used to implement the graphical illustration of the outputs.

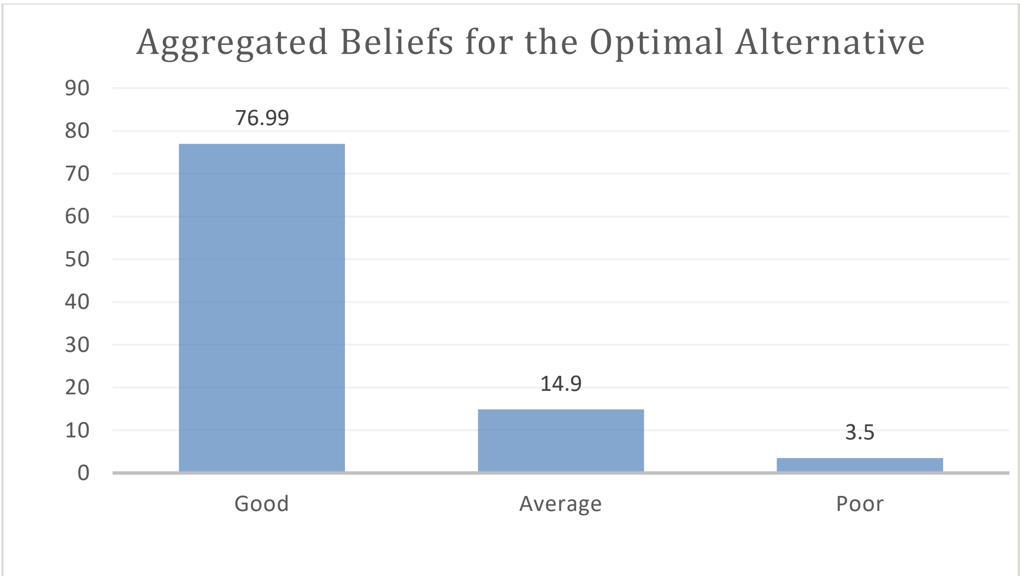

Figure 11 Example model output: Bar chart of aggregated belief for the optimal alternative

It is noteworthy that the example output reported in this section should not be construed as a recommendation for AUS management since the corresponding beliefs tensor was randomly generated. Only if AUS management provided a full beliefs tensor and ran it through the model should the literal output be considered consequential to AUS.

4.3. Model Validity

The 50 randomly generated beliefs tensors provided to Group B experts were used by the system to calculate the utilities of the alternatives, based on which the system selected optimal alternatives, as shown in Table 14. Thus, one way to validate the model would be to compare the utilities and optimal alternatives generated by the system in Table 14 to the utilities and optimal alternatives collected from the experts in Table 6. Corresponding to each beliefs tensor, the assigned expert was also asked to select the best alternative, the one with the maximum utility.

Table 14 System-generated utilities based on the beliefs tensors provided to Group B

Expert	**Utilities Generated by System**									**Output**
	A1	A2	A3	A4	A5	A6	A7	A8	A9	
1	1	0	0	0	0	0	0	0	0	A1
2	0	1	0	0	0	0	0	0	0	A2
3	0	0	1	0	0	0	0	0	0	A3
4	0	0	0	1	0	0	0	0	0	A4
5	0	0	0	0	1	0	0	0	0	A5
6	0	0	0	0	0	1	0	0	0	A6
7	0	0	0	0	0	0	1	0	0	A7
8	0	0	0	0	0	0	0	1	0	A8
9	0	0	0	0	0	0	0	0	1	A9
10	1	0	0	0	0	0	0	0	0	A1
11	1	0	0	0	0	0	0	0	0	A1
12	0.25	0.25	0.75	0.25	0.25	0.25	0.25	0.25	0.2	A3
13	0.25	0.25	0.25	0.75	0.25	0.25	0.25	0.25	0.2	A4
14	0.25	0.25	0.25	0.25	0.75	0.25	0.25	0.25	0.2	A5
15	0.25	0.25	0.25	0.25	0.25	0.75	0.25	0.25	0.2	A6
16	0.25	0.25	0.25	0.25	0.25	0.25	0.75	0.25	0.2	A7
17	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.75	0.2	A8
18	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.7	A9
19	0.5	0.1634	0.1634	0.1634	0.163	0.1634	0.1634	0.1634	0.1	A1
20	0.16	0.5	0.1634	0.1634	0.163	0.1634	0.1634	0.1634	0.1	A2

21	0.16	0.1634	0.5	0.1634	0.163	0.1634	0.1634	0.1634	0.1	A3
22	0.16	0.1634	0.1634	0.5	0.163	0.1634	0.1634	0.1634	0.1	A4
23	0.16	0.1634	0.1634	0.1634	0.5	0.1634	0.1634	0.1634	0.1	A5
24	0.16	0.1634	0.1634	0.1634	0.163	0.5	0.1634	0.1634	0.1	A6
25	0.16	0.1634	0.1634	0.1634	0.163	0.1634	0.5	0.1634	0.1	A7
26	0.16	0.1634	0.1634	0.1634	0.163	0.1634	0.1634	0.5	0.1	A8
27	0.16	0.1634	0.1634	0.1634	0.163	0.1634	0.1634	0.5	0.1	A8
28	0.42	0.5439	0.6079	0.6108	0.610	0.6946	0.5792	0.6784	0.4	A6
29	0.57	0.6784	0.4500	0.4270	0.543	0.6079	0.6108	0.6100	0.6	A9
30	0.67	0.6946	0.4270	0.5439	0.607	0.6108	0.6100	0.6946	0.5	A2
31	0.73	0.7419	0.5174	0.4291	0.642	0.6063	0.5967	0.7419	0.6	A2
32	0.42	0.5439	0.6079	0.6108	0.610	0.6946	0.5792	0.6629	0.6	A6
33	0.60	0.6108	0.6100	0.6946	0.579	0.6629	0.6794	0.1634	0.6	A4
34	0.66	0.6794	0.6079	0.6108	0.610	0.6946	0.5792	0.6946	0.1	A6
35	0.69	0.1634	0.6629	0.6794	0.607	0.6108	0.6100	0.6946	0.5	A1
36	0.16	0.6629	0.6794	0.6100	0.694	0.5792	0.6079	0.6108	0.6	A5
37	0.16	0.6629	0.6794	0.6100	0.694	0.5792	0.6079	0.6108	0.6	A5
38	0.61	0.6946	0.5792	0.6946	0.662	0.6794	0.1634	0.6784	0.6	A2
39	0.45	0.7164	0.5028	0.2502	0.833	0.6846	0.3752	0.8022	0.6	A5
40	0.42	0.7743	0.5612	0.6675	0.556	0.7972	0.6594	0.5788	0.5	A6
41	0.74	0.4974	0.8022	0.7178	0.583	0.7938	0.7703	0.4881	0.7	A3
42	0.58	0.3226	0.6114	0.5961	0.510	0.5801	0.2970	0.7478	0.3	A8
43	0.65	0.5554	0.7984	0.7171	0.493	0.6852	0.4540	0.6274	0.6	A3
44	0.27	0.6296	0.7301	0.4807	0.824	0.6564	0.2965	0.5202	0.6	A5
45	0.29	0.4630	0.5482	0.2810	0.640	0.5742	0.2129	0.8125	0.4	A8
46	0.64	0.6566	0.7785	0.6813	0.552	0.8523	0.5553	0.5315	0.6	A6
47	0.61	0.1794	0.4471	0.4104	0.307	0.4204	0.3134	0.6080	0.4	A1
48	0.49	0.4417	0.5268	0.4194	0.409	0.6432	0.4854	0.6614	0.3	A8
49	0.40	0.3355	0.4693	0.3951	0.412	0.4304	0.4186	0.5516	0.3	A8
50	0.65	0.3933	0.6088	0.3776	0.476	0.4486	0.3688	0.4576	0.4	A1

4.3.1. Raw data summary

The system was validated with a dataset of 50 truth data points. The system-generated utilities and optimal alternatives are compared to their expert-provided counterparts in Table 15.

The system-generated utilities and the expert-provided utilities of the optimal alternatives were plotted in an XY Scatter chart in Figure 12 to visualize how closely the system's results align with the experts' opinions.

Table 15 Comparison of the system's results to the experts' decisions

Test Runs	System Utility	System Results	Expert Utility	Expert Results
1	1	A1	1	A1
2	1	A2	1	A2
3	1	A3	1	A3
4	1	A4	1	A4
5	1	A5	1	A5
6	1	A6	1	A6
7	1	A7	1	A7
8	1	A8	1	A8
9	1	A9	1	A9
10	1	A1	1	A1
11	1	A1	1	A1
12	0.75	A3	0.75	A3
13	0.75	A4	0.75	A4
14	0.75	A5	0.75	A5
15	0.75	A6	0.75	A6
16	0.75	A7	0.75	A7
17	0.75	A8	0.75	A8
18	0.75	A9	0.75	A9
19	0.5	A1	0.5	A1
20	0.5	A2	0.5	A2
21	0.5	A3	0.5	A3
22	0.5	A4	0.5	A4
23	0.5	A5	0.5	A5
24	0.5	A6	0.5	A6
25	0.5	A7	0.5	A7
26	0.5	A8	0.5	A8
27	0.5	A8	0.5	A8
28	0.69	A6	0.7	A6
29	0.69	A9	0.6	A9
30	0.694614	A2	0.7	A2
31	0.741931	A2	0.75	A2
32	0.694614	A6	0.75	A6

33	0.694614	A4	0.7	A4
34	0.694614	A6	0.7	A6
35	0.694614	A1	0.7	A1
36	0.694614	A5	0.7	A5
37	0.694614	A5	0.7	A9
38	0.694614	A2	0.7	A2
39	0.83354	A5	0.8	A5
40	0.797288	A6	0.8	A6
41	0.802289	A3	0.8	A3
42	0.747877	A8	0.75	A8
43	0.798422	A3	0.8	A3
44	0.82466	A5	0.8	A5
45	0.812593	A8	0.8	A8
46	0.85234	A6	0.85	A6
47	0.612789	A1	0.6	A8
48	0.661435	A8	0.7	A6
49	0.551644	A8	0.55	A8
50	0.658589	A1	0.65	A1

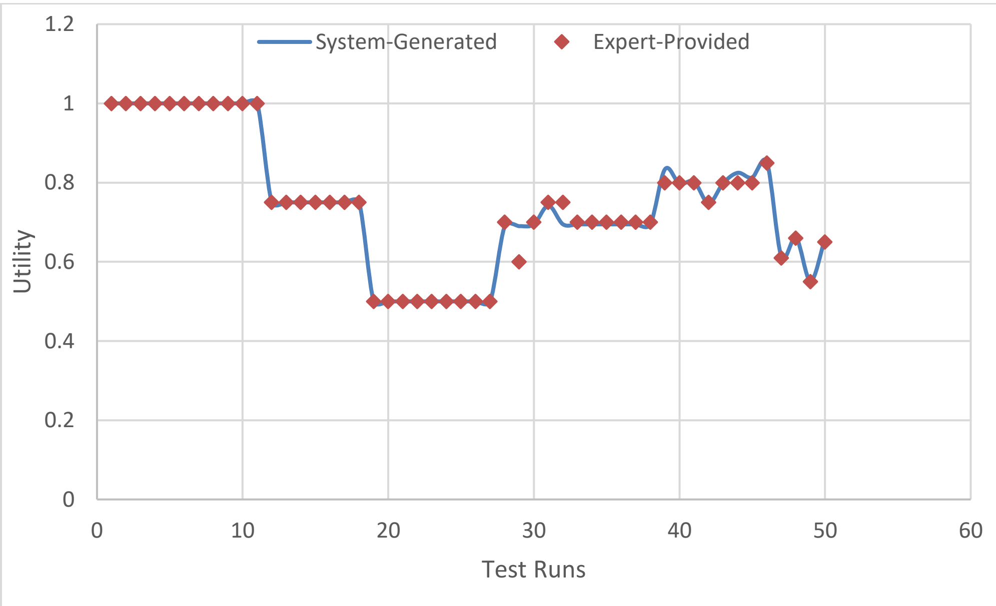

Figure 12 Comparison of system-generated utilities to expert-provided utilities

The above graph shows that the line for expert-provided utilities mostly overlaps the one for system-generated utilities for the 50 test runs. Therefore, for the given 50 cases, the proposed decision support system correctly selected almost all the optimal alternatives.

For more rigorous statistical validation of the model output, we can check whether the two distributions (expert-provided vs. system-generated utilities) are significantly different from one another with the help of the paired t-test. A favorable result would be to have no statistically significant difference between the two distributions. However, both distributions should be normally distributed before applying this statistical test. Hence, a test of normality is required.

4.3.2. Normality test

The two distributions have been plotted separately in histograms in Figure 13 and Figure 14.

It may not be obvious from the histograms whether the distributions are bell-shaped. Hence, a numerical approach to the normality test is recommended. IBM SPSS Statistics version 22 was used to test the normality of the data.

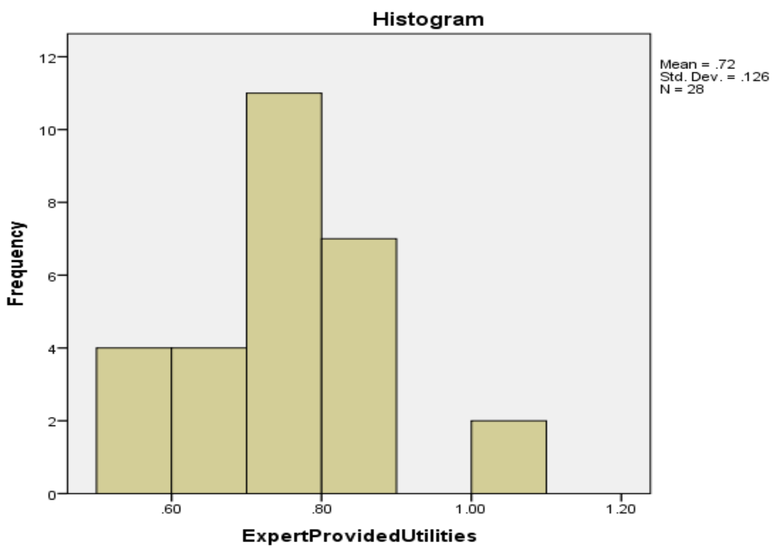

Figure 13 Histogram of expert-provided utilities

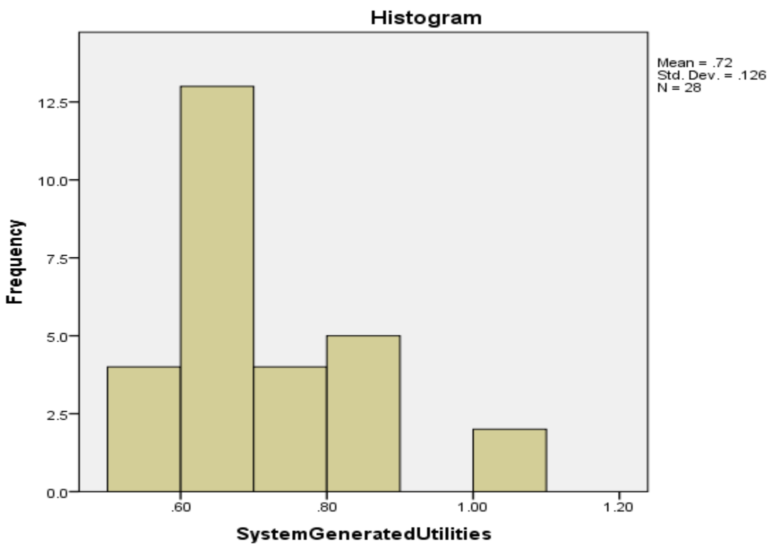

Figure 14 Histogram of system-generated utilities

The normality test was performed on both system-generated and expert-provided utilities with 50 tests per 50 cases as shown in Table 17. Table 16 also shows that there was no missing data for this test.

Table 16 Case processing summary for t-test

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
System Generated Utilities	50	100.0%	0	0.0%	50	100.0%
Expert Provided Utilities	50	100.0%	0	0.0%	50	100.0%

Table 17 Descriptive statistics of the t-test

			Statistic	**Std.**
System Generated Utilities	Mean		.7190	.02374
	95% Confidence Interval for Mean	Lower Bound	.6703	
		Upper Bound	.7677	
	5% Trimmed Mean		.7156	
	Median		.6946	
	Variance		.016	
	Std. Deviation		.12562	

	Minimum		.50	
	Maximum		1.00	
	Range		.50	
	Interquartile Range		.13	
	Skewness		.279	.441
	Kurtosis		.561	.858
Expert Provided Utilities	Mean		.7168	.02376
	95% Confidence Interval for Mean	Lower Bound	.6680	
		Upper Bound	.7655	
	5% Trimmed Mean		.7131	
	Median		.7000	
	Variance		.016	
	Std. Deviation		.12573	
	Minimum		.50	
	Maximum		1.00	
	Range		.50	
	Interquartile Range		.15	
	Skewness		.258	.441
	Kurtosis		.564	.858

The skewness values for the system-generated and expert-provided utilities were reported as 0.279 and 0.258, respectively, both of which lie between -0.5 and 0.5. Based on the skewness value, it is established that both datasets are fairly symmetrical.

The kurtosis values were found to be 0.561 and 0.564, where a kurtosis value less than 3 implies the tails are thinner than in the normal distribution and that the considered distribution's peak was lower, meaning the data is light-tailed or lacks outliers [97].

4.3.3. Paired t-test

As the sample data passed the normality test, the system could be validated using a parametric test. Thus, a paired t-test was performed to validate the system-generated results against the experts' provided truth data. Table 18 presents the results of the paired two-sample t-test.

The paired t-test for means yielded a p-value of 0.597, which is greater than the 0.05 significance level. Therefore, there is no statistically significant difference between the system-generated and expert-provided utilities. The results can be interpreted as meaning that the utilities generated by the system are very close to the utilities provided by the experts. In the following sections, the model's performance is rigorously assessed to quantify how closely it can emulate a decision-making expert.

Table 18 Results of the paired two-sample t-test for means

	System Generated Utilities	Expert Provided Utilities
Mean	0.74764618	0.7464
Variance	0.028370705	0.028460245
Observations	50	50
Pearson Correlation	0.995167299	
Hypothesized Mean Difference	0	
df	49	
t Stat	0.531646386	
P(T<=t) one-tail	0.298686545	
t Critical one-tail	1.676550893	
P(T<=t) two-tail	0.597373089	
t Critical two-tail	2.009575199	

4.4. Model Performance Assessment

The model’s performance has been assessed with the help of three powerful tools: Confusion matrices, the area under the ROC curve, and six other performance metrics.

4.4.1. Confusion matrices

The confusion matrix consists of four different measures: True positive (TP), true negative (TN), false positive (FP), and false negative (FN), best defined as in Table 19.

Table 19 Confusion matrix structure [98]

Validation	Predicted Positive	Predicted Negative
Actual Positive	True Positive (TP)	False Negative (FN) Type II Error
Actual Negative	False Positive (FP) Type I Error	True Negative (TN)

A confusion matrix with the results generated by the proposed system was developed, as shown in Table 20.

Table 20 Confusion matrix for system validation

		System Predicted Alternatives								
		A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**
Expert Provided Actual Alternatives	**A1**	6								
	A2		5							
	A3			5						
	A4				4					
	A5					6				
	A6						8		1	
	A7							3		
	A8	1							7	
	A9					1				3

Based on the above confusion matrix, four measures: True Positive, False Positive, True Negative, and False Negative, for nine different classes (alternatives) were calculated in Table 21.

Table 21 Four crucial measures for system validation

	A1	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**
TP	6	5	5	4	6	8	3	7	3
FP	1	0	0	0	1	0	0	1	0
TN	43	45	45	46	43	41	47	41	46
FN	0	0	0	0	0	1	0	1	1

From the above multi-class confusion matrix, a pooled confusion matrix [95], [96] was generated, as in Table 22.

Table 22 Pooled confusion matrix for system validation

		Predicted Value	
Actual Value		Positive	Negative
	Positive	True Positive (TP) = 47	False Positive (FP) = 3
	Negative	False Negative (FN) = 3	True Negative (TN) = 397

4.4.2. Performance metrics

Based on the four measures (TP, FP, TN, FN), more meaningful measures of model performance, such as precision, sensitivity, specificity, accuracy, and F1 score, can be calculated.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{25}$$

$$\text{Negative Predicted Value} = \frac{\text{TN}}{\text{TN} + \text{FN}} \tag{26}$$

$$\text{Sensitivity or Recall or True Positive Rate} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{27}$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN} + \text{FP}} \tag{28}$$

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{29}$$

The precision of a model determines how many cases the system identifies as positive out of all the available positive cases [99]. The negative predicted value of a model reflects how much data from all cases predicted as negative were correctly classified as negative [99]. A model's sensitivity determines the ratio of how much data was correctly identified as positive to how much data was actually positive [99].

On the other hand, specificity defines the ratio of how much data was correctly classified as negative to how much data was actually negative [99]. The accuracy indicates how much data has been correctly identified [99].

The F1 score defines the performance of the model that can be calculated using sensitivity and specificity [100].

$$\text{F1 Score or Performance} = \frac{2 \text{ x } (\text{Precision x Recall})}{\text{Precision} + \text{Recall}} \quad (30)$$

The pooled confusion matrix in Table 22 was used to determine the precision, recall, sensitivity, and specificity of the proposed decision support model, which are reported in Table 23.

The negative projected value was estimated at 0.9925, indicating that the decision support model correctly identified over 99% of negative cases, whereas the sensitivity was calculated at 0.94, as the system accurately detected 47 out of 50 predicted-positive cases.

Table 23 Overall model performance measures

Performance Measure	Value
Precision	$\frac{TP}{TP + FP} = \frac{47}{47 + 3} = 0.94$
Negative Predicted Value	$\frac{TN}{TN + FN} = \frac{397}{397 + 3} = 0.9925$
Sensitivity	$\frac{TP}{TP + FN} = \frac{47}{47 + 3} = 0.94$
Specificity	$\frac{TN}{TN + FP} = \frac{397}{397 + 3} = 0.9925$
Accuracy	$\frac{TP + TN}{TP + TN + FP + FN} = \frac{47 + 397}{47 + 397 + 3 + 3} = 0.9867$
F1 Score	$\frac{2 \times (0.94 \times 0.94)}{0.94 + 0.94} = 0.94$

The specificity of this system was 0.9925 or 99.25%. This means the system identified almost all predicted-negative cases correctly. In addition, the accuracy was found to be 0.9867, indicating that the system can accurately identify over 98% of cases.

The F1 score, the harmonic mean of precision and recall, measures the performance of a system. The F1 score for the proposed system was 0.94.

4.4.3. Receiver operating characteristics

The ROC curve is a graphical demonstration of the performance of a model [101]. It helps the user with a comparative study of different models with a particular objective. To investigate the validity of a proposed model, the ROC technique employs both mathematical and visual elements.

For more clarification of the system's accuracy, the area under the ROC curve is a metric often used to validate the effectiveness of a classifier. The ROC curve was generated using IBM SPSS V.22, as shown in Figure 15.

The ROC curve in Figure 15 demonstrates the model's sensitivity against the false positive rate, which is equivalent to 1-specificity. The closer the generated line is to the left and upper border and the further away it is from the diagonal line connecting the points (0,0) and (1,1), the better the model's performance.

To better understand the system's performance from the ROC, the area under the curve (AUC) was also calculated and reported in Table 24.

Generally, a model that performs no better than random guessing would have an AUC of 0.5, while a perfect classifier would have an AUC of 1. The area under the ROC curve for the proposed system was calculated to be 0.734, which is greater than 0.5, implying that the model performs better than random guessing.

Again, the asymptotic significance for the proposed system was found to be 0.178, which is greater than 0.05. Therefore, the developed decision support system is valid.

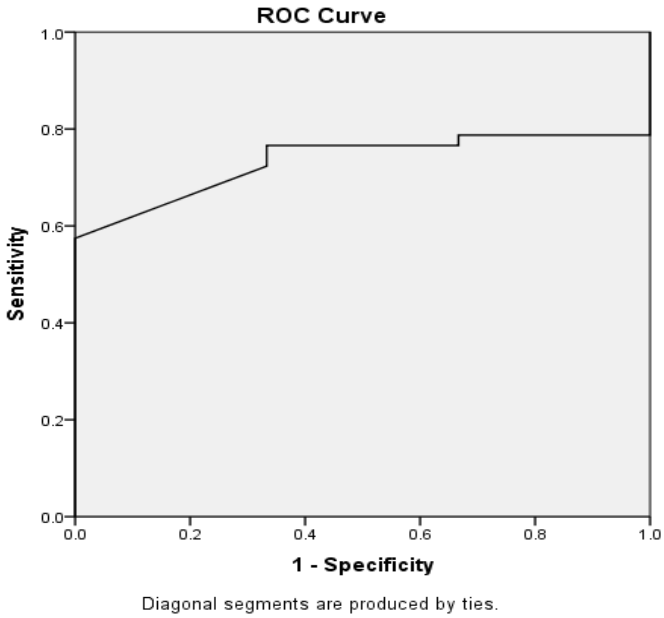

Figure 15 Receiver Operating Characteristic (ROC) curve

Table 24 Area under the ROC curve for system-generated utilities

Area		**0.734**
Std. Error (under the nonparametric assumption)		0.071
Asymptotic Significance		0.178
Asymptotic 95% Confidence Interval	Lower Bound	0.594
	Upper Bound	0.874

4.5. Conclusion

This chapter investigated the validity of two model constituents as well as outputs from the model. A rigorous performance assessment of the proposed model was conducted, too.

To validate that the alternatives are unique and non-overlapping, a two-way ANOVA test conducted on the stakeholders' responses revealed that the nine alternatives compiled by the author from the literature are significantly different in terms of user preference. This implied a valid, distinct, and non-overlapping classification of smart campus technologies.

Next, a sensitivity analysis was also conducted and showed that the attribute weights collected from Group A experts were reliable and valid.

In section 4.3.1, the results of the model were reported for 50 test runs corresponding to 50 randomly generated beliefs tensors. The utilities for each alternative were generated from the system and compared to the utilities provided by the experts based on the same 50 beliefs tensors. In section 4.3.3, the paired t-test showed that the differences between the expert-provided and system-generated utilities are statistically insignificant, even at the 0.05 significance level. This result assures the fundamental validity of the model. With a statistically valid model at hand, the next step was to assess its performance.

In section 4.4, the model's performance was assessed with the help of confusion matrices and standard performance metrics, such as precision, accuracy, F1-score, sensitivity, and specificity. Finally, the ROC curve was used to verify that the model is far superior to random guessing.

Chapter 5. Discussion and Conclusion

5.1. Summary and Discussion

Universities worldwide are attempting to transform their traditional campuses into smart ones to keep up with technological advancements. However, establishing a smart campus necessitates the deployment of several smart applications, leaving management perplexed as to which solutions to implement first, what the important success elements and anticipated benefits are. This praxis has established a generic decision-making model to assist a university's strategic management team in prioritizing any number of smart campus solutions being considered based on each university's unique circumstances.

First, it is imperative to clearly define a smart campus in terms of its objectives, solutions, underpinning technologies, and critical success factors. Through an in-depth literature survey in Chapter 2, six main objectives of a smart campus were identified: the enhancement of workflow automation, safety and security, teaching and learning, strategic management, and resource conservation. These objectives are achieved by combining four main underpinning technologies: Cloud computing, IoT, AR and VR, and AI. Those four technologies have been applied by many engineers and researchers to generate countless smart campus solutions.

Although the number of smart campus solutions in the literature and industry is overwhelming, we posited that they all could be grouped into nine families by function, as demonstrated in 2.1.3. Those nine families would later become the alternatives in an MCDA problem. Therefore, it was necessary to ensure that this categorization of alternatives is distinct and non-overlapping. Hence, a stakeholder opinion survey that involved current students, alumni, and faculty at AUS was conducted. A single-factor, two-way ANOVA test applied to the survey results revealed statistically significant differences between the ratings allocated to each functional family. This implies that the respondents understood each functional family to be sufficiently separate and independent.

Next, six critical success factors at the strategic level were also identified from the literature, namely, the three types of costs (i.e., implementation, operation, and maintenance), as well as implementation duration, resource availability, and stakeholders' perceived benefit. Those success factors were then incorporated into the MCDA problem as attributes against which each alternative is to be evaluated.

The following step was to select the most appropriate MCDA problem to apply to the smart campus strategic decision problem. The various families of decision-making frameworks were reviewed, and the Evidential Reasoning (ER) approach was selected as the most suitable among 12 surveyed MCDA methods. Not only is ER a framework that accounts for user uncertainty, but also allows for mixed qualitative and quantitative attributes to be considered. The mathematical formulation of the ER model was established in 3.4 following the Dempster-Shafer (DS) algorithm. For clarity, some calculation steps were illustrated with a simplified version of the original problem in Appendix A.

However, the model is not yet fully defined, with only alternatives and attributes. Another necessary pillar of the model is the attribute weights, which express the relative importance of the different attributes. The attribute weights were determined from a group of AUS experts that included faculty, staff, and operational managers using the Nominal Group Technique, as explained in 3.5.1, by averaging their final voted weights.

Afterward, the ER model was programmed in Python – a powerful programming language. The model accepts input in the form of a three-dimensional tensor of degrees of belief (also referred to simply as a *beliefs tensor*), where each element is a degree of belief at the intersection of an alternative, an attribute, and an evaluation grade. Consequently, the model outputs the average utility of each alternative and a ranking of alternatives in descending order of average utility. The optimal alternative would be the first alternative in the ranked list. Examples of the model outputs are illustrated in 4.2.

For the next step, the model was validated by randomly generating 50 belief tensors, running each tensor simultaneously through the model and through a group of decision-making experts. The experts provided utilities for each alternative using their experience and judgment.

The validity of the model was assessed in 4.3 with a paired t-test that revealed no statistically significant difference between the expert-provided results and the model-generated results, even at the 0.05 significance level. Furthermore, the area under the model's Receiver Operating Characteristics (ROC) curve was calculated to be 0.734, which implies that the model performs better than random guessing.

The final research objective of this work was achieved with a comprehensive performance assessment. The model's performance was evaluated in 4.4 using seven metrics, namely, accuracy, precision, sensitivity, specificity, negative predicted value, and F1 score: Each was found to be upwards of 90%, thereby lending further support to the soundness of the model and its ability to reliably emulate a decision-making expert.

5.2. Model Limitations and Future Work

Although the study successfully achieved its aim, below are some key limitations to the research, and possible areas of improvement in the future.

5.2.1. Relevance of the results

So far, the model has been validated with randomly generated degrees of belief; therefore, its outputs have no real consequences to AUS. However, it would be interesting to have AUS management provide their degrees of belief to the model and consider its recommendations for the future development of the AUS campus. In addition, in the case a university campus other than that of AUS is being considered, then the attribute weights should be updated to reflect that university's unique hierarchy of values.

Besides, it has been assumed throughout that the university's leadership is not restrained by commitment to a strategic goal, for example, "to become the most sustainable campus in the country by next year." The model may, for instance, recommend the Smart Classroom as the most optimal application, whereas leadership had already committed to cutting down wasted utilities in half by the next quarter. Thus, it is worthwhile to consider adding “Strategic Alignment” as an additional attribute to the model in the future.

Thirdly, the model outlines the digital transformation plan for a fully traditional campus. However, if the campus has already incorporated some smart applications, the decision-making tool must consider the existing smart systems by excluding them from the alternatives.

5.2.2. Cost analysis

The proposed model does not account for implicit costs, i.e., the opportunity cost of utilizing financial or human resources towards the smart campus transformation as opposed to other profitable alternatives. Currently, the model bases its decisions on explicit costs and makes no account of implicit costs, which have a role to play in altering the final utilities of alternatives and hence, influencing the decision-making process. Therefore, it is interesting to investigate how such costs could be accounted for.

Moreover, the current implementation of the model does not prompt the user for the institution’s budget and, therefore, would not exclude an alternative that exceeds the stated budget. In the future, a simple mechanism can be implemented such that alternatives whose annualized costs exceed the annual budget would be automatically excluded from the analysis.

Also, the evaluation of what constitutes a “good”, “average”, or “poor” cost has been left to the subjective interpretation of the interviewed stakeholders and management personnel, which could be a source of confusion and disagreement. In the future, more objective and concrete definitions of “Low”, “Medium”, and “High” costs should be laid out.

5.2.3. Utility assumptions

To simplify the analysis, a linearly spaced, discrete utility function has been assumed, with the utilities of the three evaluation grades evenly distributed from 0 to 1. To increase the resolution of the model, more evaluation grades may be added (e.g., “Excellent”, “Very Good”, “Good”, “Average”, “Below Average”, “Bad”, “Very

Poor”), or a continuous utility function may be assumed. This proposal, however, may come at the risk of a worse user experience, as the user would be prompted for exponentially more inputs with the addition of each new evaluation grade.

5.2.4. Ease of use

One of the limitations of this model is that it is data-intensive, as a single run of the model currently requires 162 degrees of belief to be provided, which might be quite tiresome to fill up by a small group of users in a single sitting. Therefore, a worthwhile future endeavor could be to explore ways to build the beliefs tensor with as few user prompts as possible to make the model easier and more expedient to use. Perhaps this goal could be achieved by employing an AI chatbot, or possibly, an intelligent survey design could aid in building the beliefs tensor by quantifying and inferring user sentiment.

Finally, while the degrees of belief related to the various attributes could be filled out by university management and smart campus experts, we point out that beliefs related to the “stakeholder benefit” attribute should not be filled out by management alone. For best results, the beliefs related to stakeholder benefit should consider the views of the four stakeholder categories, which are detailed in Appendix B.

However, the collaboration between management and other stakeholders is likely to uncover significant differences between their sentiments regarding what the campus urgently needs, and such conflict may hinder or prolong the decision-making process. To mitigate the risk of conflicts arising, the attribute “stakeholder benefit” could be broken down into several subsidiary attributes – each subsidiary attribute would then capture the perceived benefit of a single stakeholder category.

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Appendix A: Dempster-Shafer Example

To demonstrate the DS algorithm and clarify its definitions with an easy-to-understand example, consider a simpler version of the smart campus decision problem with just three attributes {Stakeholder's Benefit (SB), Project Cost (PC), Project Duration (PD)}, and three evaluation grades {Good, Average, Poor}, considering the alternative {Smart Classroom}.

Attribute Weight

The attributes for establishing a smart campus can be weighted as (SB, 0.5), (PC, 0.4), and (PD, 0.1), meaning that the stakeholder's benefit for establishing a smart campus is 50% important whereas PD and PC are 10% and 40 % important respectively. Symbolically, $\omega_1 = 0.5, \omega_2 = 0.4, \omega_3 = 0.1$.

Basic Degree of Belief

For example, the stakeholder's benefit can be evaluated by user as {(Good, 0.7), (Average, 0.3), (Poor, 0.0)} which means the user is 70% sure that the stakeholder's benefit from a Smart Classroom is Good, 30% sure the benefit is Average and 100% sure that benefit is not Poor at all. The 70%, 30% and 0% are the degrees of belief at each evaluation grade. Symbolically,

$$\beta_{1,1} = 0.7, \beta_{1,2} = 0.3, \beta_{1,3} = 0 \tag{31}$$

In this example, the degrees of belief for the attribute SB across the evaluation grades adds up to 1. However, this may not always be the case.

A user can provide inputs for the attribute PD for an alternative as, {(Good, 0.5), (Average, 0.3), (Poor, 0.0)}. The inputs provided imply that the user is 50% confident that the stakeholder's benefit from the alternative is Good, 30% confident that the stakeholder's benefit is Average and 100% sure that benefit is not Poor. However, the system received only 80% confidence degree from the user which leaves 20% uncertainty in decision-making system.

Basic Probability Masses

The probability mass of an attribute, e.g., PC, being evaluated as Good can be calculated as $m_{2,1} = \omega_2 \times \beta_{2,1}$.

For example, if a user is 80% sure that the PC for the Smart Campus is Good ($\beta_{2,1} = 0.8$) and if the PC is 40% important ($\omega_2 = 0.4$) in case of establishing a smart campus then, $m_{2,1}$ evaluates to $0.4 \times 0.8 = 0.32$.

If the degrees of belief for PC are considered as, (Good, 0.8), (Average, 0.1) and (Poor, 0.0) then, the unassigned mass for project cost m_2^* due to incomplete belief can be calculated as,

$$m_2^* = 1 - \omega_2 \sum_{n=1}^{N} \beta_{2,n} = 1 - 0.4\ (0.8 + 0.1 + 0) = 0.64 \tag{32}$$

m_2^* could have also been calculated as the sum of $\overline{m_2}$ and $\tilde{m}_2$, where:

$$\overline{m_2} = 1 - \ \omega_2 \ = 1 - 0.4 = 0.6 \tag{33}$$

$$\tilde{m}_2 = \omega_2 \left(1 - \sum_{n=1}^{N} \beta_{2,n}\right) = 0.4\ [1 - \ (0.8 + 0.1 + 0)] = 0.04 \tag{34}$$

Clearly, $\overline{m_2} + \tilde{m}_2 = 0.64 + 0.04 = 0.64$, which agrees with the result from (32).

In summary, the data at the basic attribute level can be summarized in the table below.

Table 25 Summary of data at the basic attribute level for the DS example

	Weight	Belief			Basic Probability Mass					
		Good	Average	Poor	Good	Average	Poor	$\overline{m}_i$	$\tilde{m}_i$	m_i^*
SB	0.5	0.7	0.3	0	0.35	0.15	0	0.5	0	0.5
PC	0.4	0.8	0.1	0	0.32	0.04	0	0.6	0.04	0.64
PD	0.1	0.5	0.3	0	0.05	0.03	0	0.9	0.02	0.92

Probability Mass Aggregation

The probability mass of the general attribute is computed using a recursive algorithm that aggregates the masses of the first two basic attributes in the first iteration, then proceeds to incorporate one basic attribute at a time in the following recursions until all basic attributes have been incorporated. To illustrate the operations performed in the first iteration, let's consider the aggregated probability mass of two attributes, SB and PC for an alternative with respect to three evaluation grades: Good, Average, and Poor.

Letting,

$$M_{1,n} = m_{1,n}$$

$$\bar{M}_1 = \bar{m}_1 = 0.5$$

$$\tilde{M}_1 = \tilde{m}_1 = 0$$

$$M_1^* = \bar{M}_1 + \tilde{M}_1 = 0.5$$

Then the normalization factor for this iteration $j = 2$ is K_2, which is calculated as:

$$\begin{aligned} K_2 = & \left[1 - \sum_{t=1}^{3} \sum_{\substack{k=1 \\ k \neq t}}^{3} M_{1,t} \cdot m_{2,k}\right]^{-1} \\ & = \big[1 \\ & - \big(M_{1,1} \cdot m_{2,2} + M_{1,1} \cdot m_{2,3} + M_{1,2} \cdot m_{2,1} + M_{1,2} \cdot m_{2,3} \\ & + M_{1,3} \cdot m_{2,1} + M_{1,3} \cdot m_{2,2}\big)\big]^{-1} \\ & = [1 \\ & - (0.35 \cdot 0.04 + 0.35 \cdot 0 + 0.15 \cdot 0.32 + 0.15 \cdot 0 + 0 \cdot 0.32 \\ & + 0 \cdot 0.04)]^{-1} = 1.0661 \end{aligned} \tag{35}$$

The aggregated probability masses in this iteration are, for each evaluation grade, as follows:

For $j = 2, n = 1$

$$\begin{aligned} M_{2,1} = & K_2\big[M_{1,1} \cdot m_{2,1} + M_1^* \cdot m_{2,1} + M_{1,1} \cdot m_2^*\big] \\ & = K_2 \, [\, 0.35 * 0.32 + 0.5 * 0.32 + 0.35 * 0.64 \,] = 0.496 \, K_2 \\ & = 0.496 * 1.0661 = 0.52878 \end{aligned} \tag{36}$$

For $j = 2, n = 2$

$$M_{2,2} = K_2\left[M_{1,2} \cdot m_{2,2} + M_1^* \cdot m_{2,2} + M_{1,2} \cdot m_2^*\right]$$

$$= K_2\,[\,0.15 * 0.04 + 0.5 * 0.04 + 0.15 * 0.64] = 0.122\,K_2$$

$$= 0.122 * 1.0661 = 0.13006 \tag{37}$$

For $j = 2, n = 3$

$$M_{2,1} = K_2\left[M_{1,3} \cdot m_{2,3} + M_1^* \cdot m_{2,3} + M_{1,3} \cdot m_2^*\right] \tag{38}$$

$$= K_2\,[\,0 * 0 + 0.5 * 0 + 0 * 0.64\,] = 0$$

M_2^* will be an input to the probability masses in the next iteration where $j = 3$, therefore, it must be computed in this iteration:

$$\bar{M}_2 = K_2\,[\bar{M}_1 \cdot \bar{m}_2] = 1.0661\,[\,0.5 * 0.6] = 0.31983 \tag{39}$$

$$\widetilde{M}_2 = K_2\left[\widetilde{M}_1 \cdot \widetilde{m}_2 + \bar{M}_1 \cdot \widetilde{m}_2 + \widetilde{M}_1 \cdot \bar{m}_2\right]$$

$$= 1.0661\,[0 * 0.04 + 0.5 * 0.04 + 0 * 0.6] = 0.021322 \tag{40}$$

Hence, $M_2^* = \bar{M}_2 + \widetilde{M}_2 = 0.31983 + 0.021322 = 0.341152$

This process continues until all the attribute masses are combined, i.e., until $j = L$, which in this simplified example, is 3.

Belief Aggregation

Once $M_{L,n}$ has been calculated for every evaluation grade, as well as $\bar{M}_L$ and $\widetilde{M}_L$, we have all the required inputs to calculate the assigned and unassigned aggregated degrees of belief for the general attribute.

The aggregated assigned degrees of belief for the general attribute for every evaluation grade as calculated as:

$$B_1 = \frac{M_{L,1}}{1 - \bar{M}_L} \tag{43}$$

$$B_2 = \frac{M_{L,2}}{1 - \bar{M}_L} \tag{41}$$

$$B_3 = \frac{M_{L,3}}{1 - \bar{M}_L} \tag{42}$$

Thus, the total unassigned degree of belief for the considered example can be calculated as,

$$B^* = 1 - \sum_{n=1}^{N} B_n = \frac{\widetilde{M}_L}{1 - \bar{M}_L} \tag{44}$$

Utility Aggregation

Had there been no unassigned beliefs, the utility for the alternative "Smart Classroom" would have been calculated as follows:

$$U = (B_1 \times 1.0) + (B_2 \times 0.5) + (B_3 \times 0.0) \tag{45}$$

However, since unassigned beliefs exist in this example, a utility range instead is calculated for the Smart Classroom alternative. The maximum utility for the Smart Classroom can be estimated as:

$$U_{\max} = \sum_{n=1}^{N} B_n u_n + B^* u_1 \tag{46}$$

while the minimum utility for the Smart Classroom can be estimated as:

$$U_{\min} = \sum_{n=1}^{N} B_n u_n + B^* u_N \tag{47}$$

Appendix B: Structure of Stakeholders in a Smart Campus

The table below shows how the four types of stakeholders are structured in a smart campus. Apart from the numerous smart technologies that can be applied to the campus, an important underlying aspect behind any smart campus' success would be the cooperative and interconnected functioning of the various stakeholders. The various contributions expected from each stakeholder and the needs of the different stakeholders are summarized in Table 26 [4].

Faculty and staff were approached to extract attribute weights, while students and staff were approached to understand whether there is a genuine need for a smart campus, and what they believe to be the most needed smart campus application. The management team is the stakeholder who shall use the model to rank the smart campus alternatives and make a decision accordingly.

Table 26 Stakeholders' roles in a smart campus transition

Stakeholders	Needs	Contributions
Current & Graduated Students	Convenient campus life High quality educational experience Guidance before entering next phase of life	Provide valuable feedback and suggestions for improvements Develop new concepts of smart campus in their research studies.
Faculty	Optimize student performance and track student progress Remain up-to-speed with the latest development in their field of research	Provide valuable feedback and suggestions for improvements Apply smart pedagogies and hence improve teaching quality Act as a coordinator and contribute to the continuous

		improvement of the smart campus.
Staff	Smart and efficient solution to handle huge administrative burdens Smart solutions for daily campus maintenance and support	Participate in the transformation to the smart campus and its subsequent maintenance. Provide technical support Analyze user needs while providing feedback Optimize the operation of the smart campus.
Management Team	More efficient and comprehensive monitoring and reporting Timely and accurate data of students, staff and competitors to help make better-informed decisions.	Make appropriate smart campus decisions while managing funds. Facilitate and coordinate internal and external university communication processes.

Vita

Mohamed Faisal Khatri was born in 1997, in Mumbai, Maharashtra, in India. He was educated in public schools in Saudi Arabia and graduated from Indian International Public School in Riyadh.

In 2014, Mr. Faisal moved to the United Arab Emirates where he pursued higher education and earned a Bachelor's Degree in Mechanical Engineering from the American University of Sharjah in 2018. During his time as an undergraduate, his extracurriculars included playing for the university's table tennis team, working as a Physics grader and as a library technical assistant at the university library. He was elected as the Treasurer for the university's American Society of Mechanical Engineers Chapter.

In 2018, Mr. Faisal began a Master's program in Engineering Systems Management at the American University of Sharjah, during which he received a full-time teaching assistant scholarship. In the final year of his Master's study, he started working as a procurement and logistics specialist at Chalhoub and currently works as a customer facing supply chain specialist at Unilever.