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Assessing and predicting the students' systems thinking preference: multi-criteria decision making and machine learning

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The 21st century is marked by a technological revolution that features digital implementation and high interconnectivity between systems across different domains, such as transportation, agriculture, education, and health. Although these technological changes resulted in modern systems capable of easing individuals' lives, these systems are increasingly complex, and that increased complexity is only expected to continue. The increased system complexity is due to the rapid exchange of information between subsystems, which creates high interconnectivity and interdependence between the subsystems and their elements. Workforce skill sets, as a result, must be modified appropriately to ensure the systems' success. Systems Thinking is an approach that helps individuals better understand and effectively solve modern complex systems problems by encouraging holistic thinking. Systems thinking consists of two approaches holistic and reductionist views. This dissertation aims to study college engineering and non-engineering students' preference for holistic thinking versus reductionist thinking, their ranking to the systems thinking dimensions, and whether this preference varies depending on demographics and general factors. Additionally, this study investigates the possibility of predicting the students' preference for holistic thinking. The study uses the multi-criteria decision-making method, the Analytic Hierarchy Process and Fuzzy Analytic Hierarchy Process to determine the student's preferences, and uses statistical analysis such as independent sample t-test and ANOVA to evaluate the factors. Also, the study uses machine learning classification models such as Logistic Regression, Support Vector Machine, Naïve Bayes, Decision Trees, voting classifiers, Bagging, and Random Forest to predict and evaluate the most predicting model. The results of the dissertation conclude that overall students prefer the reductionist approach and report the students' preference towards dimensions of complexity, independence, uncertainty, systems worldview, and flexibility and the ranking difference based on some factors. Lastly, the results show that the students' preference for holistic thinking can be predicted with a 77% accuracy using the Random Forest classifier.

DEDICATION

I dedicate this dissertation to my heroes and pillar in life, my father Dr. Azeddine Tazzit and my mother Fatiha Limouri, who supported and motivated me throughout my program. I want to thank my brother Soufiane Tazzit, my sister-in-law Zineb Ismaili, and our new member my cutie niece Sophia Tazzit. Without your unconditional love, patience, listening, and belief in me, it would have been extremely hard. I apologize for everything you had to go through because of me and not being present on some of your special occasions. Thank you for reminding me each time that “I can do it” and reminding me of my goals in life and keeping me focused. I love you deeply with all my heart and I am forever grateful for you. Simply I can’t imagine life without you. Also, I would like to say Hamdoulah for all the strength God, Allah gave me.

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CHAPTER I

INTRODUCTION

Today's modern systems necessitate the integration of digitization due to the ongoing advancements in technology and data accessibility, which has increased the difficulty of managing such complex systems. Therefore, having skillful and creative thinkers who can manage and fix these complicated systems becomes crucial and vital. To ensure the workforce has the necessary skill sets, focusing on student preparation through curriculum design will be critical to train students to be able to understand and interact with these systems. Training students to think systemically and holistically will be important in developing workers capable of operating these complex systems. Systems engineering is one of the disciplines that have helped to holistically face and mitigate complex systems' challenges. Systems engineering has evolved throughout the years and played a significant role in contributing to the design, management, and optimization of systems, which can be integrated with other skills to effectively deal with these increasingly complex systems.

Systems engineering (SE) is defined as a methodology that provides guidance for the engineering and development of complex systems (Kossiakoff et al., 2011). In other words, SE provides guidelines to design, develop, lead, manage, or direct (Kossiakoff et al., 2011). Also, Kossiakoff et al. (2011) determined that one of the major functions of SE is to help in selecting one approach among different possible ways of dealing with a complex system (Kossiakoff et al., 2011). SE differs from the other disciplines as it is considered an interdisciplinary field that help to ensure the success and realization of a complex systems (Walden et al., 2015).

Systems Thinking (ST) is an approach that suggests the wholeness view to understand the interaction between the parts of complex systems and managing how the system functions as a whole (Waldman, 2007). ST is an essential skill for individuals, especially students, to identify, solve, and address complex systems' problems. This dissertation investigated engineering and non-engineering students' system thinking as a way to understand, predict, and improve the student's learning experience and prepare future generations capable of tackling complex challenges.

This chapter outlines the content and motivation of the dissertation. To establish the research plan for a dissertation, many researchers rely on the theoretical frameworks. This dissertation uses the theoretical framework developed by Osanloo and Grant (2016). The framework uses different constructs to define the research approach described by Osanloo and Grant (2016): Problem, Purpose, Significance, Research Questions, Theoretical Framework, and Method.

1.1 Problem statement

The abundance of information and the continuous development of technology has created an increase in the complexity of the systems' problem solving and decision making. The increase in systems complexity challenges the ability of engineers to effectively and efficiently solve modern complex systems. Integration, ambiguity, uncertainty, complexity, evolutionary development, and interdependence are some characteristics of modern complex systems. In order to overcome the challenges of modern complex systems, there is a need for an alternative approach to the conventional problem-solving approaches. Several researchers suggest holistic thinking/systemic thinking to ease the understanding of these systems such as Senge (1990), Hossain et al., (2020), Amissa et al., (2020). ST is considered not only an approach to facilitate the handling of these complex systems but also an essential skill for systems engineers or engineers in general to understand the root causes of the problems within these systems. Future engineers must have the knowledge, abilities, and expertise required to design, create, and practice innovative and sustainable solutions to satisfy society's demands that incorporates ST. This requires a comprehensive training program that focuses not only on technical knowledge but also on developing critical thinking, communication, and problem-solving skills. Over the past several years, a surge in development technology has led to an increase in demand of workers and engineers in several educational fields, especially fast-growing engineering specialties such as SE. As a result, many college students choose to pursue their degrees in engineering due to the variety of available fields that suit and fit their interests. Therefore, it is imperative to focus the students' learning experience in both technical and non-technical aspects to ensure their ability to fit in and perform their future tasks as intended (Hossain et al., 2020; Hagen and Bouchard, 2016). ST skills are considered not only helpful in dealing with complex systems but also in assessing the capabilities of engineering and non-engineering college students to integrate both their technical and non-technical skills.

ST has been the topic of several research papers across different fields that encompass complex systems, such as transportation, healthcare, energy, education, and many others. Over the years, ST has proven its effectiveness and importance in these fields, especially education. For this reason, the main objective of the dissertation is to focus on both engineering and non-engineering students enrolled in bachelor's, master's, or doctoral programs to explore their preferences regarding ST approaches to mitigate complex systems effectively. In other words, this dissertation will examine the own preference and inclination of the students towards the holistic or reductionist view. Investigating the judgement of the students is important as it will help to understand the student's own perspectives to determine which approach resonates more with them and their thought processes while handling complex systems. Ultimately, this provides valuable information for educational institutions to support them in effectively shaping their curriculum and teaching method to enhance students holistic thinking. Also, one of the goals of the dissertation is to investigate the possibility of using ST skills to integrate them with machine learning to examine the possibility of predicting students' preference for the holistic or reductionist ST view. We have compiled a list of the study's objective, as follow:

- Determine the students' preference to ST overall approaches Holistic or Reductionist thinking.
- Determine the priority preference to the seven dimensions of ST.
- Predict the students' preference using machine learning techniques.

1.2 Purpose

As these past years have been marked by continuous increases in the level of system complexity, an increased need for having a skillful workforce able to manage and solve complex systems has been evident. Having workers, even multidisciplinary teams, capable of holistically thinking about a system, capable of understanding and detecting the root causes of the problems are critical. Therefore, the purpose of this study is twofold. The first fold consists of investigating students' preference toward ST skills viewpoints, namely holistic/systemic or reductionist/less systemic. This investigation will help to enhance comprehension of how students perceive and tackle complex systems, and shed light on their cognitive processes. Furthermore, the first fold also involves evaluating differences in ST preference among the students based on various factors these preferences is needed to show how these facts affect the complex systems attribute preference of the students. The second consists of predicting the students' preference of overall ST approaches using the outcome of the first fold.

1.3 Significance

A thorough literature review reveals a gap in integrating ST in the education field. The gap is related to determining the student's level of ST skills enrolled in engineering college. Beyond that, the literature reveals the absence of exploration in the subject for the student's own preference on ST skills approaches to the contrast of their assessment only. Additionally, the thorough literature review showed that little attention is paid to the integration of ST and machine learning to build models capable of predicting and determining students' preferences. Thus, this dissertation is considered significant as it attempts to fill and address the current gaps in the literature. The contribution of each section is noted in the following chapters. The first section of the methodology chapter will start by investigating the student's inclination for ST, particularly whether they tend to prefer a holistic approach that looks at the system as an entire system or a reductionist approach that looks at the components of the system. Additionally, the section examines the student's ranking of the seven dimensions used to describe the ability of the individual to deal with a complex system based on their specific demographic or general information. The objective is to understand the student's perception and own thoughts of ST to offer insightful data that can contribute to adequately helping the students to enhance the levels that necessitate further attention. The next section of the methodology will address implementing machine learning into ST. This will provide additional insights concerning the ST skills of the students, as its main objective is to study the prediction of the students' preference for systemic/less systemic views based on the seven dimensions and demographic factors and general attributes (i.e., gender, learning modality, GPA, the program of study, major of study, and current year of study (for bachelor's students)) using machine learning modeling techniques. This implementation can be beneficial as it can be used as a guide to better assist, guide, and mentor new students. Additionally, since ST is also highly related to the performance of the students, predicting the ST preference can indirectly help to enhance their school performance as well. As noted in the recent research paper of Pallathadka et al. (2021), understanding the students' performance beforehand will help to understand the areas that require further attention and improvement.

1.4 Research questions

In line with the two main objectives of the dissertation and the research gaps in the literature, hypotheses have been developed to explore ST for the students enrolled in college. Different research questions with sub-questions are established.

The developed hypotheses are the following:

H1: ST preference of the students are affected by demographic and/or general factors.

H0: ST preference of the students are not affected by demographic and/or general factors.

H1: ST preference of the students can be predicted using machine learning techniques.

H0: St preference of the students cannot be predicted using machine learning techniques.

To address the developed hypotheses, the following research questions are built to serve as a base for the dissertation:

1. What is students' perception of systems thinking skills?
    a. What is/are the most important dimension (s) of systems thinking?
        i. What are the ranking and most important/preferred dimensions of systems thinking to the students based on gender?

ii. What are the ranking and most important/preferred dimensions of systems thinking to the students based on their learning modality?

iii. What are the ranking and most important/preferred dimensions of systems thinking to the students based on their GPA?

iv. What are the ranking and most important preferred dimensions of systems thinking to the students based on the degree program of study?

v. What are the ranking and most important/preferred dimensions of systems thinking to the students based on their major of study?

vi. What are the ranking and most important/preferred dimensions of systems thinking to the bachelor's students based on their current year of study?

b. What is the overall preference of the students? Is it holist thinking or reductionist thinking?

i. What is the overall preference base on gender?

ii. What is the overall preference based on the learning modality?

iii. What is the overall preference based on GPA score?

iv. What is the overall preference based on the degree program of study?

v. What is the overall preference based on the major of study?

vi. What is the overall preference for bachelor's students based on their current year of study?

c. Is there a significant relationship between the students' preferences for the systems thinking dimensions and general factors, including gender, learning modality, GPA, program of study, major of study, and current year of study for bachelor's students?

2. Can students' systems thinking holistic or reductionist preference be predicted?

   a. What model can best predict students' holistic preference based on the seven dimensions and demographic factors?

1.5 Theoretical framework and method

The progress of society undoubtedly requires the active cooperation and development of holistic thinkers. Therefore, it is vital for colleges and universities to help build well-trained citizen-leaders that mitigate the insurmountable issues of complex systems (Grohs et al., 2018). The aim of the study consists of the two previously described objectives that are divided into two parts, and each part is represented by a respective main research question with sub-questions. The dissertation is organized in the following manner: Literature review, Methodology, Results, and Conclusion.

Chapter II of the dissertation, Literature Review, provides an overview of ST theory, the available instruments that are used to measure ST, and the impacting factors that affect ST. The goal is to introduce the importance of the concept along with the previous research studies that align with the proposed dissertation.

Chapter III of the dissertation, Methodology, provides the data analysis plan of the dissertation. It is divided into two sections. Because the dissertation investigates an abstract and theoretical concept, the optimum manner of collecting the data is through survey design. For this reason, the first section discusses the data collection, which includes the survey design, the procedure of the survey, the data collection, and the data description to provide further information about the population of the study. The second section of the methodology provides the data analysis methods used to study the research questions. The data analysis includes the Analytical Hierarchy process, the Fuzzy Analytical Hierarchy Process, and Machine Learning that contains supervised models such as Logistic Regression, Support Vector Machine, Naïve Bayes, Decision Tree, and ensemble learning (Voting classifier, Bagging, and Random Forest).

Chapter IV of the dissertation, Results, provides the results obtained using the analysis techniques to answer the proposed research questions.

Lastly, Chapter V of the dissertation concludes with a discussion and summary of the findings along with the limitations and future research directions.

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

The world has been undergoing continuous improvement and development over the past few decades, which has resulted in an abundance of information and an increase in the complexity of systems. In line with different researchers, new modern systems are marked to be complex as they include different characteristics (i.e., the high level of uncertainty, ambiguity, interconnectivity, and interrelation) (Hosssain et al., 2020; Nagahi et al., 2019; Nagahi et al., 2020; Jaradat, 2015). Hence, the literature stresses the importance of adapting new techniques that combine technical and non-technical skillsets to complement, support, and manage complex problem-solving. While some systems' problems can be solved using simple and traditional methods, these methods are revealed to be less effective in solving complex systems (Pennock and Wade, 2015). Therefore, as the new systems are becoming more and more comple with time, conventional SE approaches such as direct cause-effect analysis are no longer sufficient to deal with these systems (Flood, 2010; Kossaiakoff, 2011; Henshaw, 2019). For this reason, various researchers have pointed out that successful decision-making and effective problem-solving of the current complex systems require a holistic approach to view and deal with these systems (Hossain et al., 2020; Monat et al., 2022). One of these techniques and skills that has been suggested as a complement to traditional problem-solving of these new systems is Systems

Thinking (ST). Hence, ST can be used as a supporting technique or a bridge to move from theory to practice.

Since Bertalanffy brought attentions to the necessity for a general theorem to be applied in various disciplines to traverse complex systems, the idea of ST has been in the researchers' eyes for more than 50 years (Bertalanffy, 1968). Numerous scholars have concentrated on characterizing ST skills ever since the theory's inception. For instance, ST is defined by Checkland as the cognitive proof that demonstrates the ability to understand and address complex systems by perceiving and thinking in a holistic way (Checkland, 1981). In other words, ST is viewed as a new method that helps assist, manage, and solve complex systems' decision-making problems for different disciplines, including environmental, educational, and medical. Numerous applications and integrations of ST have been made in the academic field. Due to the prevalence of dynamicity, self-organization, and ongoing adaptability in today's society, it is crucial to adequately equip and prepare engineers to deal with complex system.

This section of the dissertation is organized in such a way as to introduce the concept of ST: background including definition of system and ST, applications of ST, related factors to ST, and instruments used to assess the level of ST. The last subsection will conclude with literature gaps and the suggested analysis.

2.2 Background of systems thinking

Since the word "systems thinking" is composed of the word "system" and the word "thinking," a definition of system is necessary to understand the theory behind it.

2.2.1 Definition of system

The definition of the system or “what is a system” has been responded based on the concept of its use in Francois’ International Encyclopedia of Systems and Cybernetics development, only to know that the definition has raised enormous confusion and lack of agreement between the users (Taylor et al., 2020). For this particular reason, the definitions provided were not commonly used (Taylor et al., 2020). In order to address this confusion and lack of agreement, the “Ontology of Systemology” was developed by Rousseau and his colleagues to unify the definition of systems (Taylor et al., 2020). The framework consists of a guideline to identify and detect that the item underhand is actually a system, to characterize the components of the system, to understand the importance of the system such as its use of function and the properties of the systems (Taylor et al., 2020; Rousseau et al., 2018).

Rousseau et al. (2018) defined a system to be under two main categories. As explained by Taylor et a. (2020), the first category is a concrete system that consists of a persistent structure or persistent process, while the second category is a conceptual system that consists of a persistent meaning characteristic. In Rousseau’s framework, these two types of systems are the fundamental systems and can be used such that the interaction between their construct and component can build in a new particular system (Rousseau et al., 2018). Likewise, Meadows (2008) identified a system by its collection of parts. This definition is also available in the Merriam-Webster dictionary, which defines the system as a collection of interacting or independent group of items forming a whole (Merriam- Webster’s online dictionary, n.d.). Like most definitions of systems, a system consists of boundaries that permit to delimit and separate the system from its environment. The definition of the system was also one of the tackled topics of Jackson in chapter 1 of his book “Systems Thinking: Creative holism for Managers,” where he defined a system to be a complex whole that consists of different components that interacts with each other's (Jackson, 2016).

2.2.2 Definition of systems thinking

As previously defined, ever since the birth of ST, different researchers have focused on determining a definition for it. One of the most popular definitions of ST is the one by Senge (1985). He emphasized on the holistic view as he defined ST to be the discipline that encourages looking at the system through its interrelationship between the elements and recognizing the patterns of the system (Senge, 1990). Along the same context, Richmond also suggested a definition for ST to be the manner in which the individual can develop a reliable inference and conclusion through an extensive understanding of the underlying structures (Richmond, 1994). Other scholars have addressed the definition of ST and linked it to complexity, such as Sweeney and Sterman (2000). They suggested that ST requires a list of skills to describe and evaluate the dynamic complexity of systems (Sweeney and Sterman, 2000). Arnold and Wade (2015) describe ST as a "system of thinking about systems", while Meadows (2008) construct a definition that relies on 1) the elements or characteristics, 2) the interrelation or interaction between the elements, 3) and the functions of systems. The potential power of ST is its inter-disciplinary nature that can be used in different fields to study a concept or an idea, is the definition provided by Jackson (Jackson, 2016). Although numerous definitions of ST exist in the literature, the most commonly used and author-agreed definition consists of the approach that supports thinking about systems as a whole by looking at the interrelationship between the components and looking at the system as a whole. Overall, after defining the system and understanding that ST is a multi-disciplinary concept, it is necessary to look at its applications, domains, and prior research studies, which will be discussed in the next section of the literature review.

2.3 Application of systems thinking

Over the years, technological advancements and rapid development have resulted in complex systems that require skilled and well-trained individuals to service and manage them. Hence, traditional skills are no longer sufficient, and a transition to a more holistic approach is required, as Hossain et al. (2020) described. The holistic view, the big picture, and the relation between elements, such definitions of ST, are mainly applied in engineering (Castelle and Jaradat, 2016; Bahill and Gissing, 1998; Frank and Elata, 2005; Senge, 1990). ST skills are one of the approaches that researchers suggest to serve and be used in conjunction with conventional systems engineering methods. This leads to the importance of implementing ST across different domains such as economy, management, environment, health, ecology, chemistry, and many others (Orgill et al., 2019; Iacovidou et al., 2021; Nagahi et al., 2020; Trbovich, 2014). For example, over 25 years, ST has been applied in the healthcare sector significantly and increasingly (Jackson and Sambo, 2019). A body of research is exploring this topic and related ST to the health system (Burke and Pestotnik, 1999; Jackson and Sambo, 2019; Leischow et al., 2008; Wong et al., 2010). For instance, Adam and Savigny (2012) determined the need for a new approach to deal with the health system's complexity to have better achievements. In their study, they suggested the use of ST as a way to tackle the interrelationship of the systems as well as to reorient the mindset of the individuals through developing new skills that support: dynamic thinking, systems-as-cause thinking, forest thinking, operational thinking, and loop thinking (Adam and Savigny, 2012). Within the same sector of the health system, Dommermuth and Ewing (2018), the study stressed the importance of ST and the integration of multidisciplinary team for success in this domain. Sustainability is one field that has used ST (Adams et al., 2016; Onat et al., 2017; Williams et al., 2017). For illustration, Rebs et al. (2018) relate the use of ST and propose a conceptual framework to look at sustainable supply chain management by taking into account the interconnectivity and interaction of the elements that are within the system. ST has also appeared in human resource-related studies (Cavana et al., 2007; Brinkerhoff et al., 1994). ST is proposed as a strategy in combination with multi-criteria decision-making techniques for job recruiting, as suggested in the study of Karam et al. (2020). Recently, ST has also been applied in virtual reality (Dayarathna et al., 2021; Dayarathna et al., 2021; Jaradat et al., 2019).

Education is among the other and most important fields in which ST has been applied. Therefore, different practitioners in the area concentrated on ST and education. For instance, Assaraf and Orion focused on junior high school students to determine their capability to deal with complex systems, the influencing factors, and the relationship between the ST's cognitive components (2005). The study showed the existence of a hierarchical structure that represents the stages of ST development and an improvement in ST for most of the studied sample size. The progress of the student's level of ST skills was affected by their cognitive abilities and engagement effort during the learning experience (Assaf and Orion, 2005). Similarly, under business programs, specifically MIS, a study attempted to emphasize the importance of ST to help Information Systems professionals in mitigating complex systems from the design to the simulation but also the modeling (Vo et al., 2006). Hopper and Stave (2008) evaluated the effectiveness of ST skills in education for K-12 students. The authors' study was based on three prominent folds: defining ST, determining the applied interventions, and analyzing the measurements of the used interventions (Hopper and Stave, 2008). Along the same lines, Davis et al. (2015) proposed a conceptual model that aims to help increase people's performance in the context of leadership in community college. The suggested model includes three stages discovery, framing, and action (Davis et al., 2015). Within the same framework of community colleges, Naghi et. (2020) focus on engineering students to assess their level of ST skills and links their proactive personality to study their impact on the student's performance (Nagahi et al., 2020; Nagahi et al., 2020). A recent study by Dugan et al. (2022) showed the importance of comprehensive ST skills by focusing on assessing the students in engineering by using previous assessments (Dugan et al., 2022). Fisher (2023) studied ST and system dynamics on pre-college students to show the importance of introducing ST to students and its benefit on precollege students. The case study has demonstrated that using ST improves student engagement and analytical skills since it facilitates identifying the systems and analyzing their complex features (Fisher, 2023).

2.4 Relationship between systems thinking and other factors

In many studies, the authors highlighted the significance of ST and its benefits in improving the understanding of complex systems and supporting the mitigation of the individual's job duties across different domains such as industrial engineering, project management, process improvement, and many others (Olszewski, 2014; Karam, 2020). Naturally, individuals inherently possess diverse cognitive processes and different approaches to problem-solving (Whyness and Sach, 2007). Therefore, individuals' approach and attitude toward a system may be different based on the individuals' perception and other factors. Identifying these factors will not only deepen the understanding of the student's profile and manner of approaching a system but will also help to encourage critical thinking.

Different research studies have focused on determining the factors that affect the level of ST skills. Gender difference is one of the investigated subjects to test whether the males and females are similar or different in their approaches (McConkey, 1992; Stephens, 2012; Yigermal, 2017). Midgley (2000) studied the impact of gender on systems intervention, while Stephens (2012) studied the same but on the critical thinking of ST. Furthermore, Lewis (2016) investigated gender differences and critical ST in her dissertation to conclude that in order to improve the business of the stakeholders, there is a need for a structured systemic intervention "Gendered Systemic Analysis." In a recent research study, Nagahi et al. (2019) investigated the effect of gender on ST skills for practitioners holding the title of engineering manager, systems engineer, and manager. Using Structural Equation modeling, the results of Nagahis' study revealed that the total of 206 males versus 52 females shows a significant difference in both levels of systems worldview and change in contrast to the other levels of interaction, independence, uncertainty, complexity, and flexibility (Nagahi et al., 2019). Along the same line, a study of Stirgus and his colleagues determined the impact of the following factors the level of education, the status of employment, the internship, and grade point average GPA on the level of ST of 50 engineering students. The results revealed that only the employment status significantly impacts the ST level (Situgus et al., 2019). Sladek et al. (2010) examined gender differences in the healthcare sector. Using Relational Experiential Inventory (REI), the manner of thinking and disposition among males and females are contrastingly different. Hence, the findings showed that men and women generally prefer a distinct way of thinking (Sladek et al., 2010). On the other hand, other prior results of research papers concluded that students' academic performance is highly correlated to the level of ST skills (Huang et al., 2015; Weiser and Riggio, 2010). Race and gender were factors studied by Ohland and his colleagues, who found that people from different races and genders responded differently even when faced with the same situation or circumstances (Ohland et al., 2017).

In addition to gender and ethnicity, age is another factor that may affect the level of ST. For instance, Friend and Zubek (1958) used the Watson-Glaser Critical Thinking Appraisal test to reveal the influence of age on people's critical thinking. Camelia and Ferris (2016) studied the students' ST engagement using two surveys with a distinct version of questionnaires. The study examined differences in students' engagement based on gender, age, number and years of work experience, and the country of the university. The finding showed that gender differences did not significantly affect ST compared to other factors (age, year of work experience, and country of the university) (Camelia and Ferrris, 2016).

In addition to the general demographic factors and academic performance (GPA), other attributes were studied to see their impact on ST, such as family background and school environment. Many studies focused on students' performance and ST as they are highly related. For example, Lauer and Lauer (1991) and Amato and Keith (1991), tackled the impact of the parental situation of the students on their academic success. Both publications reached similar conclusions that parents directly influence the success of the student. Apart from the parental situation, reports have shown that social impacts a person's critical thinking. According to the manuscript of Cheung et al. (2001), students from upper-class families tend to show better critical thinking abilities compared to students from lower-class families. The outcome permit to deduct that students from less privileged families can show a lack in critical thinking that can be caused by a lack of resources.

Another additional factor also supported in the literature is student-professor interaction. According to Cokley et al. (2004), the students' ST skills are influenced by the type of interaction with their professor. In other words, the quality and frequency of the students' interaction with the professor can significantly impact the students' development. Analogous research by Chickering and Reisser (1993) presented that students' ST capability is not only dependent on their engagement but is also related to their interaction with the school environment. The research indicated that the educational institution's competence, engagement, involvement, and wiliness enhance the student's ST abilities (Chickering and Reisser, 1993). Similar findings are supported by Umbach and Wawrzynski (2005), who stressed the importance of faculty members and professors to collaborate in the enhancement of students' performance and the development of their engagement.

The study of the influencing factors is a focus of the researchers because it represents a potential manner to improve systemic thinking. Different scholars have investigated this topic, such as Gero and Zach (2014) who performed a longitudinal study over three years period to determine the improvement of ST for high school students. The results of the research proved that students' performance and ST is enhanced by the end of the studied period (Gero & Zach, 2014). Correspondingly, Assaf and Orion (2010) found that junior high school students demonstrate a learning pattern with a significant improvement in acquired ST skills, even years after. Glissen et al. (2019), using the student learning approach: observations and students' worksheets on (15-16) year old students, showed in their research that the introduction of ST helped students improve their understanding. These studies' results align with those obtained in both et al. (2017) and Gilbert et al. (2018) studies.

Although ST is important and holds numerous benefits, a scarce number of research studies investigated the possibility of predicting the ST of the individual. For instance, Yakubu and Abubakar (2022) used machine learning modeling to predict student failure and to determine the potential factors that successfully contribute to this prediction. In the study by Hussain and Khan (2021), machine learning regression and classification models were used to predict students' marks and grades respectively. In a recent research article by Mbunge et al. (2022), the objective of their study is to predict the performance of the students, determine the risks of students withdrawing from school, observe the cognitive preference and any uncommon learning behavior of the students under the Covid-19 circumstance. Vital et al. (2021) used machine learning models to classify students based on their learning abilities, teaching methods, and training abilities, along with other factors. The study uses five different machine learning algorithms for the prediction of students' performance.

Taking into consideration all aforementioned research studies, it is clear that ST is a topic that has been given high importance. Researching different factors and their influence on students' ST engagement and level requires further attention.

2.5 Systems thinking assessment techniques

With the recognition of systems complexity and problem-solving, the literature review shows that different researchers have addressed the lack of assessment tools by developing ST measuring techniques such as (Taylor et al., 2020; Gray et al., 2019; Timofte and Popus, 2019; Jaradat, 2015; Keynan et al., 2014). These measurement techniques allow us to assess and measure the level of ST skills of the individuals to help understand their capability to approach such complex systems. The proposed measuring techniques differ and can be categorized as qualitative, quantitative, or a combination of both. For illustration, Lavi et al. (2019) and Lavi et al. (2020) suggested a conceptual model, more precisely a rubric, to measure the level of ST skills called the Systems Thinking Assessment Rubric (STAR). The STAR scoring system relied on the use of Object-Process Methodology. According to Lavi et al., the STAR is unique as it is based on formal methodology and consists of 8 attributes, of which seven are shown to be the most suitable ST attributes (2019). The eight attributes are Intended purpose, Main function, Complexity levels, Main object and its sub-objects, Structural relations, Procedural relations, Procedural sequence, and Temporary objects and decision nodes (Lavi et al., 2019). The authors precise the need for further refinement and validation (Lavi et al., 2019). In order to address the ST assessment for graduate students, Grosh et al. (2018) developed a scenario-based tool. Based on their analysis of 93 freshman engineers (first-year students), the researchers suggest a tool structured around seven main dimensions. The dimensions for ST skills are 1) problem identification, 2) information needs, 3) stakeholder awareness, 4) goals, 5) unintended consequences, 6) implementation challenges, and 7) alignment (Grohs et al., 2018). Likewise, SysTest, which stands for Systems Thinking Test, is an ST tool created by Tomko and his colleagues in 2017 to measure the level of ST skills of individuals (Tomko et al., 2017). Another instrument that focuses on the holistic thinking definition for ST is the seven dimensions tool developed by Jaradat (2015). The assessment measures the level of ST skills and reports the individuals' ST profile. The instrument is based on seven different dimensions level of complexity, level of independence, level of interaction, level of change, level of uncertainty, level of systems worldview, and level of flexibility (Jaradat, 2015). These seven dimensions describe the way individuals respond and manage complex systems. The level of complexity refers to the capability of the person to analyze and understand the system to determine the root cause of the problem and the constraints. The level of independence refers to the manner in which the person tends to make decisions, either dependent or independent but also to approach a complex problem. The level of interaction refers to the person's own preference for the work environment that can be versatile (i.e., multi-cultural). Also, this level determines the way the person interacts and coordinates with the team. The level of change determines the tolerance of the person to the change that happens in the system, as complex systems are on continuous change and development. Also, this level looks at the behavior of the individuals towards new opportunities (i.e., technologies, solutions, …). The level of uncertainty refers to the ability of the individual to work in an environment that is uncertain due to the incomplete knowledge of the entire system and to not get overall fixated on the details. The second before last is the level of systems worldview; this level refers to the ability of the person to look at the systems in a big-picture manner and avoid the "cause-effect" analysis. Lastly, the level of flexibility refers to the person's ability to accommodate and adjust to the uncertainties, change, and emergence while being open to new ideas. The dissertation provides further information about this instrument in the methodology section. Although the literature revealed the existence of numerous tools to measure and assess the level of ST skills of the individual, the seven dimension skillset instrument is extensively used. The seven dimension theory combines both qualitative and quantitative data for analysis and is reliable, which explains its use by different researchers (Nagahi et al., 2021; Hossain et al., 2020; Jaradat et al., 2017; Castelle et al., 2016; Lawrence et al., 2019; Stirgus et al., 2019; Keating et al., 2021; Hossain et al., 2020).

2.6 Conclusion and proposed theoretical model

After examining the literature review, it is clear that ST is an important skill that helps individuals to develop the necessary skills to successfully manage and effectively deal with complex systems' problem solving in various domains. Also, the literature permits to conclude that ST is not only helpful for the workforce (e.g., managers, engineers, entrepreneurs), but it is also crucial to introduce it in the younger generations and students. This approach and investment are believed to help build a skillful workforce equipped with the necessary knowledge and tools to solve complex problems and contribute positively in their work environment. The development of future citizens, or “systems citizens” as referred by Dr. Richmond (Benson, 2007), who can successfully adapt to a changing and evolving world is possible and easier when holistic thinking is introduced. Holistic thinking permits to facilitate decision making as identifying the interrelationship and interdependencies between the systems’ elements becomes a lot easier.

Various scholars agree on the importance of introducing ST at all level of schooling (i.e., elementary, high-school, college, and university). While there is literature on ST and its impact on students and the measurement of their ST level**, there is no research study that has examined the preference of the students to understand their favored ST approach, using Jaradats’ developed instrument**. For this particular reason, this proposed study will focus on students as its target population to determine the preference of engineering and non-engineering students for holistic or reductionist thinking. Understanding students’ preferences will help promote better guidance and effective support from educators. Additionally, **there exists no specific research paper that attempted to find the most favored dimension or facet of ST that the students prefer**. Therefore, to fill this gap the study aims to investigate the students’ most favored dimension and rankings of the seven dimensions of ST using the instrument developed by Jaradat. By understanding how students rank in these seven dimensions will help to understand which exact level requires further support and attention. Although there are numerous research papers that investigated the effect of several factors on ST, to the best of our knowledge, **no particular study has yet explored the students’ own preference based on the factors (gender, distance or on-campus student, ethnicity, GPA, degree (bachelors, masters, or doctoral), year of study (freshman, sophomore, junior, and senior), and the major)**.

Therefore, the third objective of this dissertation is to examine the differences between those holistic/reductionist and seven-dimension preferences based on these different factors. By investigating students' preference for ST across these different factors, it is possible to understand how gender, learning modality (i.e., on-campus or distance), academic background and performance of the student affect and contribute and influence their decisions. This information obtained can help ease through the understanding of the preferences of the students. Also, it is intended to improve the success rate of the students since the educators can gain direct insights into the points (dimension or dimensions) that need further development. Another objective of this research study is to investigate whether students' preference for holistic view changes during the bachelors based on their year of study (freshman till senior), as most previous research studies target high school level students. Finally, as far as our research shows, **there hasn't been any particular study that attempted to predict whether a student prefer holistic thinking or reductionist thinking**. Therefore, because of the importance and benefits of predicting students' preferences holistic or reductionist view, this paper will aim to develop different models that can predict these preferences using ST and demographic and general factors. The dissertation offers a unique perspective to the pool of the literature as it attempts to study whether machine learning approaches provided with our used dataset are effective in predicting the holistic preference. This contribution is considered to be beneficial as it helps to classify new students into to the holistic or reductionist category, measures their comfort with holistic thinking, predict their performance, and provides adaptive assistance. This can aid in identifying students who need special accommodation, support, and attention to enhance their learning experience and improve their systemic thinking.

CHAPTER III

METHODOLOGY

3.1 Introduction

This chapter of the dissertation endeavors to provide a detailed description of the data collection procedure to illustrate the survey design, procedures, and materials. Furthermore, the chapter provides an overview of the methods employed, including the Analytic Hierarchy Process (AHP), Fuzzy Analytic Hierarchy Process (Fuzzy AHP), and machine learning algorithms.

3.2 Data collection

3.2.1 Survey design

The proposed dissertation uses survey design as its main research strategy. The survey design includes a thorough description of the demographic samples of interest, which are specifically the students. Since the study includes theoretical and abstract notions of ST in addition to demographic factors, the best method to collect and test the data is through a survey design approach. Since one of the primary objectives of the dissertation is to investigate the own students' preferences and perception of ST skills, a scale survey design is the most appropriate. The adopted survey is the AHP questionnaire type, consisting of 1 to 9 scale. Similar to the Likert scale questionnaire design, which is one of the author's agreed survey designs, as noted by Van et al. (2004), the AHP is easy to use and interpret since the decision makers are able to assign meaningful values to the compared criteria. The questionnaire is a 9- point scale representing a collection of possible responses, either numerical or verbal, to express various views or satisfaction on a subject from one extreme to another. The survey of the dissertation was developed using the Qualtrics survey design platform “https://www.qualtrics.com/”.

The purpose of the study is to investigate the students’ preference towards the holistic or the reductionist approach of ST and to rank the seven dimensions of ST used instrument. The dimensions and approaches of ST are listed in Table 3.1. In order to rank and determine the most important dimensions, a pairwise comparison of the dimensions is required. Therefore, questionnaires were developed using a pairwise comparison technique to establish prioritization and comparison. Since the data analysis is performed using the AHP multicriteria, this method required the identification of the criteria and the alternatives that serve as a guide for the questions’ development. The methodology chapter provides more information and details about the AHP multi-criteria decision-making approach. Hence, the survey included 21 questions related to ST that represents the comparison between the seven different dimensions, 7 questions related to the comparison between ST overall approaches, and finally, 7 questions related to the demographic factors. The survey asks the participants about their preference for each dimension relative to the others; participants select the relative importance of a 9-point scale. For more details about the questionnaire, please refer to the Appendix A. For illustration, one item asks, “How is the level of complexity important to you compared to the level of independence, interaction, change, uncertainty, systems worldview, and flexibility?” as a way to determine the importance of the first dimension of complexity. Correspondingly, to determine the importance of the second dimension, the participants are asked, “How is the level of independence important to you compared to the level of interaction, change, uncertainty, systems worldview, and flexibility?” In order to determine the importance of the third level of interaction compared to the other dimensions, the participants are asked, “How is the level of interaction important to you compared to the level of change, uncertainty, systems worldview, and flexibility?” Using similar approach, the fourth, fifth, sixth, and seventh dimensions are compared. The participants are asked, “How is the level of change important to you compared to the level of uncertainty, systems worldview, and flexibility”; “How is the level of uncertainty important to you compared to the level of systems worldview, and flexibility?”; and finally, “How is the level of systems worldview important to you compared to the level of flexibility?” These questions permit us to judge the preference of the students regarding the seven dimensions and their relative importance.

In order to measure the importance of holistic and reductionist views based on the preference of the students, the students answer the pairwise comparison between all seven pairs of the seven dimensions. One of the item questions asks, “In the level of complexity, how is simplicity more important to you compared to complexity?” The answer determines the importance of the Complexity versus Simplicity pair. It specifies the comfort of engaging with complex systems. The second item question asks, “In the level of independence, how is autonomy important to you compared to integration?” The answer of the participant specifies the preference for degrees of independence in dealing with multiple or internal systems and mitigating complex systems as an integrated unit. The third item question asks, “In the level of interaction, how is isolation more important to you compared to interconnectivity?” The responses of the participant permit us to understand the individual’s preferences for the environments that suit most and prefers to work in. The fourth item question asks, “In the level of change, how is resistance to change more important to you compared to tolerance to change?” The answer of the participant determines the preference to adapt to or resist change. The fifth item question asks, “In the level of uncertainty, how is stability more important to you compared to emergence,” the answer reflects the preference of the participant to deal with complex systems that are more stable, or that requires decision-making while having incomplete information. The next item question asks, “In the level of systems worldview, how is reductionism more important to you compared to holism?” The participant's response reflects their preference on how to deal with complex systems and apply holistic thinking and look at the systems as a whole or prefers to look at each part of the systems on its own. Lastly, the final item asks, “In the level of flexibility, how is rigidity more important to you compared to flexibility?”

3.2.2 Procedure

The designed survey, described in the previous section, was implemented in a web-based survey platform called Qualtrics. The research study was approved by University Institutional Review Board IRB with approval number IRB-22-508. The statistical population of this research is students of Mississippi State University in the United States, enrolled in Project Management and Engineering Economy classes, as both classes include students from different backgrounds and majors. The survey starts with a consent form to inform the students that participation is voluntary and anonymous. The consent form also includes the compensation the students receive when completing the survey. Once accepting and agreeing to the consent form, the students will access the survey. As some students may not have a prior understanding of ST, an introduction to the concept was necessary. For this reason, the survey includes the definition of ST skills, the instrument used, and the definition of each dimension. The survey is divided into three sections. After the consent form, the first section is about general demographic factors. General demographic factors, including gender, age, online/on-campus learning modality, ethnicity, GPA, degree of the program (bachelor, master, or doctoral), and major of study. The second section concerns the pairwise comparisons of the dimensions (criteria), followed by the pairwise comparisons of the holistic and reductionist approaches of each dimension (alternatives).

3.2.3 Material

The current study uses an analysis based on a validated and approved system thinking skills tool developed by Jaradat (2015). The ST instrument is based on a grounded theory that uses qualitative and quantitative theories. The ST skillset instrument is based on 39-item ST questionnaire to measure the ST across seven dimensions (shown in Table 1.1) (Jaradat, 2015, Jaradat et al., 2017). The seven dimensions are complexity, independence, interaction, change, uncertainty, systems worldview, and flexibility. These seven dimensions of the instrument include the main attributes necessary to determine the capability of an individual to mitigate modern complex systems. ST is important because it encourages the systemic view of individuals from different fields, such as healthcare, environment, transportation, and others previously described, especially for individuals who constantly deal with modern complex systems.

According to Jaradat (2015), the 39-item questionnaire allows the participant to select their most suitable answer among two predefined ones. Each dimension has 5 or 6 measurement questions. With the use of these seven dimensions and a scoring mechanism, the level of engagement of the individual on ST, the systems thinking skills score (STSS), is determined. The measured score for each dimension is mapped on the continuum scale of ST skills, represented by two opposing categories ranging from Reductionist to Holistic. For illustration, the level of flexibility, which consists of either rigid or flexible (the last dimension presented in Table 3.1), measures the comfort of the individual to accommodate alternative plans. For the presented dissertation, we use these seven dimensions and Holistic/Reductionist views to investigate the preferences of the students and their ranking from most important to least important.

Table 3.1 ST Skills Definition of seven dimensions

Dimension	Reductionist (less systemic)	Holistic (more systemic)
***Level of complexity*: Comfort with multidimensional problems and limited system understanding**	**Simplicity (S):** Avoid uncertainty, work on linear problems, prefer the best solution, prefer small-scale problems	**Complexity (C)**: Expected uncertainty, work on multidimensional problems, prefer a working solution, and explore the surrounding environment.
***Level of Independence*: Balance between local-level autonomy versus system integration**	**Autonomy (A):** Preserve local autonomy, a trend more toward an independent decision and local performance level.	**Integration (G):** Preserve global integration, a trend more toward dependent decisions and global performance.
***Level of Interaction*: Interconnectedness in coordination and communication among multiple systems**	**Isolation (N):** Inclined to local interaction, follow a detailed plan, prefer to work individually, enjoy working in small systems, and interested more in cause-effect solution.	**Interconnectivity (I)**: Included in global interactions, follow a general plan, work within a team, and interested less in an identifiable cause-effect relationship
***Level of Change*: Comfort with rapidly shifting systems and situations**	**Resistance to change (V):** Prefer taking few perspectives into consideration, over-specify requirements, focus more on internal forces, like short-range plans, tend to settle things, and work best in a stable environment.	**Tolerance of Change (Y)**: Prefer taking multiple perspectives into consideration, underspecify requirements, focusing more on external forces, like long-range plans, keeping options open, and working best in a changing environment.
***Level of Uncertainty*: Acceptance of unpredictable situations with limited control**	**Stability (T):** Prepare detailed plans beforehand, focus on the details, uncomfortable with uncertainty, believe the work environment is under control, and enjoy objectivity and technical problems.	**Emergence (E)**: React to situations as they occur, focus on the whole, be comfortable with uncertainty, believe the work environment is difficult to control, and enjoy non-technical problems.

Table 3.1 (Continued)

Dimension	Reductionist (less systemic)	Holistic (more systemic)
***System Worldview*: Understanding system behavior at the whole versus part level**	**Reductionism (R):** Focus on particulars and prefer analyzing the parts for better performance.	**Holism (H)**: Focus on the whole, interested more in the big picture, and interested in concepts and abstract meaning of ideas.
***Level of Flexibility*: Accommodation of change or modifications in systems or approach**	**Rigidity (D):** Prefer not to change, like determined plans, not open to new ideas, and motivated by routine	**Flexibility (F)**: Accommodating to change, like a flexible plan, open to new ideas, and unmotivated by routine.

Adapted from (Jaradat, 2015)

3.2.4 Data description

The participants in the study are recruited from Mississippi State University. A small PowerPoint presentation was conducted for the Project Management class to introduce ST, and for the Engineering Economy class, a survey link was posted on the school Canvas. A total of 372 were included in the study, ranging from 18 to 62 years old. The distribution of the respondents' gender was 273 male and 99 female. The sample population came from different backgrounds. The most frequent ethnicity was White/Caucasian, followed by Black/African, Asian, Multiracial, Middle Eastern, and some other ethnicities or prefer not to disclose. The participation includes both On-campus and Online students, while On-campus students are more frequent. Table 3.2 represents the data description to include all the sample characteristics.

Table 3.2 Sample Characteristics

Variable	Category	Number (Frequency percentage)
Gender	Female	99
	Male	273
Age	17-19	84 (22.6%)
	20-29	261 (70.2%)
	30-39	18 (4.6%)

Table 3.2 (Continued)

Variable	Category	Number (Frequency percentage)
	40-49	6 (1.8%)
	50-59	2 (0.5%)
On-campus vs. Online	On-campus	307 (82.5%)
	Online	65 (17.5%)
Ethnicity	Asian	16 (4.3%)
	Black/African American	33 (8.9%)
	Caucasian	299 (80.4%)
	Middle Eastern	2 (0.5%)
	Multi-racial	7 (1.9%)
	African/North African	2 (0.6%)
	Other	1 (0.3%)
	Prefer not to say	9 (2.4%)
GPA	4.00	58 (15.6%)
	3.50-3.99	150 (40.4%)
	3.00-3.49	103 (27.7%)
	2.50-2.99	50 (13.4%)
	2.00-2.49	10 (2.7%)
	1.50-1.99	1 (0.3%)
	0.00-1.49	-
Degree of program	Bachelor's degree	297 (79.8%)
	Master's degree	70 (18.8%)
	Doctoral degree	5 (1.3%)
Bachelors' degree	Freshman year	41 (11.0%)
	Sophomore year	80 (21.5%)
	Junior year	110 (29.6%)
	Senior year	65 (17.5%)
Major of study	Aerospace Engineering	9 (2.4%)
	Biomedical Engineering	22 (5.9%)
	Chemical Engineering	33 (8.9%)
	Civil Engineering	47 (12.9%)
	Computer Science	39 (10.5%)
	Educational Engineering	1 (0.3%)
	Electrical Engineering	27 (7.3%)
	General Engineering (MENG)	1 (0.3%)
	Industrial and Systems Engineering	72 (19.4%)
	Master Business Administration MBA-PM	39 (10.5%)
	Mechanical Engineering	64 (17.2%)
	Military Engineering	1 (0.3%)
	Petroleum Engineering	2 (0.5%)

Table 3.2 (Continued)

Variable	**Category**	**Number (Frequency percentage)**
	Software Engineering	13 (3.5%)
	Other	3 (0.8%)
Variable	Category	Number (Frequency percentage)

3.3 Data analysis

The purpose of this section is to provide a description of the different analysis techniques used to analyze and study the data of this dissertation. The first subsection concerns the data analysis using the Multi-Criteria Decision Making (MCDM) technique, the Analytic Hierarchy Process, to investigate students' preferences towards ST skills dimensions and holistic versus reductionist view. The following subsection discusses the second supporting MCDM, the Fuzzy Analytic Hierarchy Process. The next subsection concerns the study's second objective, which investigates the possibility of predicting students' preferences using machine learning techniques. Brief descriptions include Logistic regression, Support Machine Vector, Naïve Bayes, Decision Trees, and ensemble learning, including Random Forest, voting classifiers, and bagging.

3.3.1 Analytical Hierarchy Process

One of the dissertation's goals is to use the Analytic Hierarchy Process (AHP) to select and determine the most important approach and dimensions of the students' ST skills. AHP is one the most powerful, simple, and reliable multi-criteria decision tools that were developed in the 1980s by Saaty (Saaty, 2008). Thomas Saaty defined AHP as a technique that uses the knowledge of experts to establish the priority ranking by assessing and contrasting options based on pairwise comparisons. The AHP method can be used to facilitate and support complex decision-making (Forman and Gass, 2001). The AHP method's hierarchy structure allows the measurement and synthesis of various variables in a complex decision-making process in a hierarchical way, simplifying combining the parts (de FSM Russo and Camanho, 2015). AHP methodology consists of three primary functions "structuring complexity, measurement on a ratio scale, and synthesis" (Forman and Gass, 2001). These three main functions make the AHP analysis method a tool that can be used in different fields and applications. Froman and Gass (2001) define the first function of AHP, structuring complexity, because it permits to describe the manner in which humans deal with the complexity that is through the hierarchical structuring of complexity into homogeneous clusters of factors. The second function of AHP, measurement on a ratio scale, is defined because it allows obtaining proportional ratio-scale measures or prioritization of the factors used. The ranking priorities or weights of these hierarchical factors are obtained using pairwise comparison. The hierarchical organization of the factors is important because each factor's weight is obtained by calculating the product of the weight of the factor by the weight of its parent factor. For the last function of the AHP, this method allows to measure and synthesize the factors when the problem contains a significant number of dimensions that are challenging for humans to handle.

Ever since the introduction of AHP, different scholars have adopted this multicriteria method in their analysis across different domains. For instance, Li et al. (2019) studied skyscraper safety by comparing different factors and subfactors using AHP. In a study on sustainability, Kaymaz et al. (2022) use the AHP method to determine the ranking of the sub-criterion and criterion regarding the socio-economic structure of Erzurum City using experts' opinions. Akbar et al. (2022) study the code recommendation system to determine the challenges and factors that negatively contribute to the system. They rely on the use of the fuzzy AHP, which is an extension of AHP, to study the 19 identified challenges. Unlike the existing papers in the literature, which ignore the needs of the users themselves, Zhu et al. (2022) use the AHP to study the user's experience of mobile baking. Additionally, Naseer et al. (2022) examine China's environmental regulation and green economy, and efficiency to rank the identified alternatives, sub-criteria, and criteria.

To ensure appropriate and effective decision-making using the analytic hierarchy method, the decision-makers or stakeholders need to specify first the problem to solve and its objective, then determine the criteria and sub-criteria (when available) to evaluate the possible alternatives. Saaty (2008) determines the process of the AHP and organizes it in the following steps:

- Define the problem to be solved, its main objective, and the main required information.
- Establish the decision hierarchy from top to bottom. The top refers to the main goal, followed by the criteria and sub-criteria, and the alternatives.
- Create the pairwise comparison matrices that are constructed by comparing each element from the higher level to its immediate bellow element. In other words, compare the elements that share the same parent.
- Find the resulting priorities from the comparisons that are used to weigh the priorities of the level directly below it, which needs to be performed for all elements. Then, add the weighted values for each element in the level below to determine its overall or global priorities. This process is repeated until reaching the final priorities at the lowest level of the hierarchy.

In order to perform the comparison between the elements, Saaty (1980) proposes a scale that facilitates paired comparisons for humans. Table 3.3 represents the scale used to compare the elements.

Table 3.3 The fundamental scale and its description for AHP

Relative Importance	**Definition**	**Explanation**
1	Equal importance	Two activities contribute equally to the objective
3	Weak importance of one over another	Experience and judgment slightly favor one activity over another
5	Essential or strong importance	Experience and judgement strongly favor one activity over another
7	Demonstrated importance	An activity is strongly favored and its dominance is demonstrated in practice
9	Absolute importance	The evidence favoring one activity over another is the highest possible order of affirmation
2,4,6,8	Intermediate values between the two adjacent judgments	When compromise is needed
Reciprocals of above nonzero	If activity *i* has one of the above nonzero numbers assigned to it when compared with activity j, then j has the reciprocal value when compared with *i*	
Rationals	Ratios arising from the scale	If consistency were to be forced by obtaining n numerical values to span the matrix

Adapted from Saaty (1980)

Using the scale in Table 3.3, an $n \times n$ matrix is constructed, where n is the number of elements in the group. The elements are placed in the header row and columns of the matrix, as in equation (3.1):

$$A = \begin{array}{ccccc} Elements & X1 & X2 & \dots & Xn \\ X1 & 1 & x_{12} & \dots & x_{13} \\ X2 & x_{21} & 1 & \dots & x_{23} \\ \dots & \dots & \dots & \dots & \dots \\ Xn & x_{n1} & x_{n2} & \dots & 1 \end{array} \tag{3.1}$$

Where x_{ij}=1/x_{ji}, x_{ik}* x_{kj}= x_{ij} , and $x_{ii} = 1$. These properties ensure reciprocity, consistency, and homogeneity. The comparison matrix can be built by only comparing $n \times (n - 1)/2$ respecting the reciprocity property of the AHP method (Marufuzzaman and Ahsan, 2009). Because of the decision maker's subjective decision, inconsistency in the judgment may arise. The inconsistency in the judgement exists because the decision maker needs to compare different elements in succession with a set of other elements to build the comparison matrix. This inconsistency can be evaluated by finding the consistency ratio of the matrix that should be within a threshold of 0.10 (Marufuzzaman and Ahsan, 2009; Skibniewski and Chao, 1992).

The filled comparison matrix, as shown in equation (3.1), contains the upper-triangle that is the reciprocal of the lower-triangle. The highest eigenvalue from the eigenvector of the matrix is determined in order to calculate the consistency ratio using the following equations (3.2), and the consistency ratio using equation (3.3):

$$Consistency\ Index\ (CI) = \frac{largest\ eigenvalue - n}{n - 1} \tag{3.2}$$

$$Consistency\ Ratio\ (CR) = \frac{CI}{RI} \tag{3.3}$$

RI is the Random Consistency Index (RI), a constant parameter that depends on the number *n* of elements (Toknomo, 2006). RI can be determined using Table 3.4.

Table 3.4 Random Consistency Ratio

n	***1***	***2***	***3***	***4***	***5***	***6***	***7***	***8***	***9***	***10***
RI	0	0	0.58	0.9	1.12	1.24	1.32	1.41	1.45	1.49

Adapted from (Toknomo, 2006)

3.3.2 Fuzzy Analytical Hierarchy Process

In order to support the accuracy of the results obtained from the AHP analysis, the fuzzy Analytic Hierarchy Process is used as a supporting analysis. Ever since the introduction of the analytic hierarchy process, AHP has been extensively used in the literature. Soon after the introduction of the AHP, both Van Laarhoven and Pedrycz (1983) and Buckley (1985) suggest extensions of this multi-criteria decision method using fuzzy logic and geometric mean. The new extension is called Fuzzy Analytic Hierarchy Process, Fuzzy AHP, or FAHP. Fuzzy AHP permits solving the problem of uncertainty that may arise while conducting the pairwise comparison process but also the intermediate numbers that can't be assigned. Hence, the concept of the fuzzy triangular membership allows us to solve the vagueness that the decision makers, the students, may have.

Fuzzy AHP has gained popularity among scholars as it has been used across different domains. Among the areas of use of the fuzzy AHP is for supplier selection (Kilincci and Onal., 2011; Chan et al., 2008, Jain et al., 2018), service evaluation (Bakir and Atalik, 2021), site selection (Kuo et al., 1999; Kuo et al., 2002, Sasikumar and Ayyappan, 2019), project selection (Mahmoodzadeh et al., 2007), factor evaluation and prioritization (Lin et al., 2009), quality management (Lam et al., 2008; Nguyen, 2021; Ganguly, 2020). Fuzzy AHP is also suitable for ranking and preferences. Goswani and Bahera (2021) use the Fuzzy AHP to select the optimal smartphone among ten others based on seven criteria (i.e., price, storage, and battery). In the same selection and ranking factors context, AlHumid et al. (2019) use the Fuzzy AHP to evaluate different performance indicators that affect the municipal solid waste management system in Saudi Arabia. Correspondingly, Anggrainingsih et al. (2018) use Fuzzy AHP to rank the most important factors that affect the success of the implemented E-learning in the academic system. In their study, different decision-makers are involved: the students, experts of e-learning, and lecturers. These listed studies are only highlights of the existing research papers that utilized Fuzzy AHP in their respective areas. Many other papers use Fuzzy AHP in various other fields, as Chan et al. (2019) noted in the bibliometric review paper that provided the number of published papers that use the term of Fuzzy AHP that reached 4,600 in 2018.

The procedure of the Fuzzy AHP consists of first defining the goal, criteria, and alternative. The first step permits building and then decomposing the problem's hierarchy structure. The hierarchy structure of the problem starts from the top down, in which the first level is the goal of the decision-making, the middle level is the criteria, and the bottom level is the alternatives of the problem related to the middle level.

To scale the data and construct the comparison matrix, the following Table 3.5 is used (Ayhan, 2013). The triangular fuzzy numbers are used instead of the crisp values to construct the matrix in contrast of the original AHP analysis.

Table 3.5 Fuzzy Scale for Fuzzy AHP

AHP Preference Number	**AHP Linguistic Variable**	**Triangular fuzzy numbers Scale**	**Triangular fuzzy reciprocal Scale**
1	Equally Important	(1,1,1)	(1,1,1)
3	Moderately More important	(2,3,4)	(1/4, 1/3, 1/2)

Table 3.5 (Continued).

AHP Preference Number	AHP Linguistic Variable	Triangular fuzzy numbers Scale	Triangular fuzzy reciprocal Scale
5	Strongly More Important	(4,5,6,)	(1/6, 1/5, 1/4)
7	Very Strong More Important	(6,7,8)	(1/8, 1/7, 1/6)
9	Extremely More Important	(9,9,9)	(1/9, 1/9, 1/9)

Adopted from (Abdul et al., 2020)

In the third step of the Fuzzy AHP process, the comparison matrix is formed as shown in equation (3.4) using the scale presented in Table 3.5; for which x_{ij}^{a} represents the weight provided by the decision maker to show the preference of criterion or alternative *i* over the criterion or alternative *j*.

$$\tilde{A}^{a} = \begin{bmatrix} elements & X1 & X2 & \dots & Xn \\ X1 & \tilde{x}_{11}^{a} & \tilde{x}_{12}^{a} & \dots & \tilde{x}_{1n}^{a} \\ X2 & \tilde{x}_{21}^{a} & \dots & \dots & \tilde{x}_{2n^{a}} \\ \dots & \dots & \dots & \dots & \dots \\ Xn & \tilde{x}_{n1^{a}} & \tilde{x}_{n2}^{a} & \dots & \tilde{x}_{nn}^{a} \end{bmatrix} \tag{3.4}$$

The values of the $\tilde{x}_{ij}^{a}$represents the fuzzy triangular number (l_{ij}, m_{ij}, u_{ij}) where *l*, *m*, and *u* represent the lowest, average, and upper values as present in Equation (3.5).

$$\tilde{x}_{ij}^{a} = \left(l_{ij}, m_{ij}, u_{ij}\right) = (min\left(x_{ij}^{a}\right), average\left(x_{ij}^{a}\right), max(x_{ij}^{a}) \tag{3.5}$$

For illustration, the third decision maker thinks that the second criterion is very strong and more important than the fifth criterion, then $\tilde{x}_{25}^{3} = (6, 7, 8)$. Next, the average of the preferences can be computed when more than one decision maker is involved in producing one final aggregated decision.

In the fourth step of the Fuzzy AHP process, the fuzzy geometric mean of fuzzy comparison values for each criterion is calculated as shown in Equation (3.6).

$$\tilde{r}_i = \left(\prod_{j=1}^{n} \tilde{x}_{ij}\right)^{\frac{1}{n}} for\ which\ i = 1,2, \dots n \tag{3.6}$$

The fifth step of the Fuzzy AHP procedure consists of computing the fuzzy weights for each criterion by calculating the product of each $\tilde{r}_i$ with reverse vector, as shown in Equation (3.7).

$$\widetilde{w}_i = \tilde{r}_i \otimes (\tilde{r}_1 \oplus \tilde{r}_2 \oplus \dots \oplus \tilde{r}_n)^{-1} = (lw_i, mw_i, uw_i) \tag{3.7}$$

The next step in the AHP procedure is the de-fuzzification of the fuzzy weight w_i using the Center of Area method (Ahyan, 2013; Rachid et al., 2020; Helmy et al., 2021). The following Equation (3.8) shows the manner to compute the non-fuzzy weight.

$$W_i = \frac{lw_i + mw_i + uw_i}{3} \tag{3.8}$$

Equation (3.9) is used to normalize the weight since W_i represents the non-fuzzy and non-normalized weight to permit the comparison and the ranking of the alternatives.

$$N_i = \frac{W_i}{\sum_{i=1}^{n} W_i} \tag{3.9}$$

3.3.3 Machine learning

Machine learning (ML), deeply rooted in applied statistics, uses inference and pattern recognition rather than explicit or straightforward sets of rules or requirements to create computational models. The concept of Artificial Intelligence (AI) was first proposed by Turing in 1950 (Dramsch and Soren, 2022). As shown in Figure 3.1, machine learning is considered a branch or subset of AI.

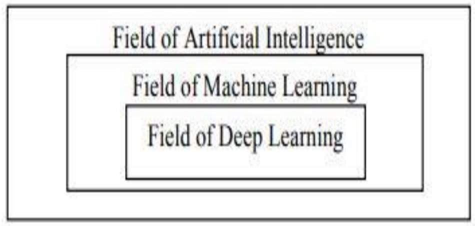

Figure 3.1 Machine learning as a branch of Artificial Intelligence
Adapted from Shunde and Shah (2018)

The word “Machine Learning” was first named by Samuel in 1959. Samuel (1959) defines machine learning as “the field of study that gives computers the ability to learn without being explicitly programmed.” Another popular definition of machine learning was provided by Tom Mitchell in 1997, who defines ML as “A computer program is said to learn from experience E with respect to some class of task T and performance measure P if its performance at tasks in T, as measured by P, improves with experience E (Mitchell et al., 1997).” This implies that a machine-learning model is determined by a combination of criteria. When performing classification, regression, or clustering, models are strengthened by conditioning them on a training set (Dramsch and Soern, 2022). The performance of the model is evaluated in relation to a loss, which measures how well the machine learning model performed on a given data. This measure permits to determine the data misfit from the predicted values in a regression implementation. Commonly, with exposure to more data, the model gets better. An optimum model generalizes to the unseen data that is not part of the training set, called the testing set, on the same task the model was trained to perform. Machine learning integrates numerous mathematical and statistical techniques and concepts such as Bayes’, least square, Markov, and many others (Dramsch and Soern, 2022).

One of the earliest and first applications of machine learning was for spam filters. Over the past few years, machine learning has been widely used in different fields and for different applications to predict, cluster, or classify. Namely, among the domains of application of machine learning are agriculture (Meshram et al., 2021; Sharma et al., 2020), robotics (Takahshi et al., 2017; Wang and Siau, 2019), medicine (Kang et al., 2015; Rajkomar et al., 2019; Quazi, 2022), finance and economy (Barboza et al., 2017), telecommunication (Smys, 2019; Mahmoud and Ismail, 2020; Ahmad et al., 2019), and many others. The education sector is also one of the areas where machine learning is being applied (Verma et al., 2022; Yakubu and Abubakar, 2022; Arashpour et al., 2023). For illustration, in a recent report by Kaddoura et al. (2022), they performed a systemic review to reveal the important role that machine learning has in the lockdown exam management systems during the Covid-19 students' examination. Pallathadka and his colleagues emphasized the significance of predicting students' performance and classification of their classification based on their skills (Pallathadka et al., 2021). The study relied on the use of Naive Bayes, SVM, and other techniques to predict the student's performance in a course based on specific factors. The results revealed that students' talent and interest, in addition to prior academic results, are good predictors for the performance of the individuals. Similarly, Yousafzai et al. (2020) applied classification machine learning techniques to predict the grade of the students for intermediate-level and secondary-level students. Along the same line, Yakubu and Abubakar (2022) investigated the possibility of predicting the student's academic performance using different indicators in order to classify the success of the students.

In addition to the various studies which focused on prediction and classification, other researchers have investigated machine learning techniques and determined the most appropriate and suitable ML models. For example, Sin and Muthu (2015) revealed that the most suitable machine-learning techniques to use for educational data are logistic regression, nearest neighbor, clustering, and classification. Rusli et al. (2008) compared different models and revealed that Neuro-fuzzy model performs better than the artificial neural network and logistic regression. To the contrast of the previous findings of Rusli and his colleagues, Shahiri and Wahidah (2015) suggested that artificial neural network performed better than decision tree, Naïve Bayes, and Support Machine Vector.

This section of the methodology section aims to introduce the different machine learning models used in the dissertation, namely logistic regression, support machine vector, Naïve Bayes, decision tree, and ensemble learning (i.e., random forest, voting, and bagging).

3.3.3.2 Logistic regression

Logistic regression is a commonly used machine learning technique that permits to classify based on the estimated probability of the class of the new data point. Logistic regression uses one or multiple sets of explanatory variables to make predictions. The probability cutoff is 50%, in other words, if the probability is above 0.5, the data point belongs to class 1; otherwise, if the probability is below 0.5, the new data point belongs to the other class. Logistic regression uses equation (3.10) to estimate the probability, or the predicted outcome, which is a value that ranges between [0, 1].

$$\hat{p} = h_\theta(X) = \sigma(\theta^T X) \tag{3.10}$$

Logistic regression converts the results of a linear equation into a probability value between 0 and 1 by using a mathematical operation called the logistic function. The logistic regression algorithm calculates the log-odds of the predicted outcome by estimating the coefficients of the variables used. The log odds are then transformed using the logistic function to obtain a probability value.

The logistic regression uses the logistic function "σ", which is an *S*-shaped curved function as shown in Figure 3.2 representing the logistic equation (3.11).

$$h_{\theta} = \frac{1}{1 + e^{-\boldsymbol{\theta X}}} \tag{3.11}$$

where $\boldsymbol{\Theta}$ is the parameter to optimize, and $\boldsymbol{X}$ be the vector of independent variables used as input.

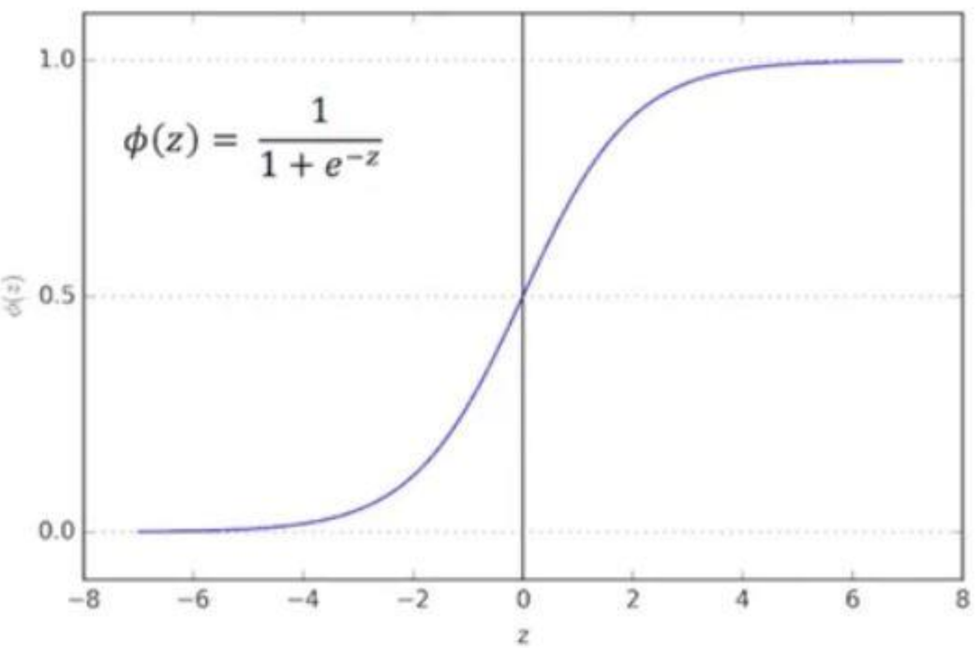

Figure 3.2 Logistic function

Adapted from Wagh (2021)

After estimating the probability of $\hat{p}$ using the logistic regression model to determine to which class **X** belongs to, the predicted probability of $\hat{y}$ can be determined using equation (3.12).

The predicted probability will be set to 0 and 1 according to the cutoff of 50%.

$$\hat{y} = \begin{cases} 0 & if\ \hat{p} < 0.5 \\ 1 & if\ \hat{p} \geq 0.5 \end{cases} \tag{3.12}$$

As seen in equation 3.10 the objective of training the model aims to determine the optimal **ϴ** to obtain high probabilities for instances that are close to *y = 1*, and low probabilities for instances close to *y = 0* (Geron, 2019). The resulting output is the predicted value, where a value closer to 1 implies that the instance is more likely to be a sample for which *y = 1*. On the other hand, a value closer to 0 implies that the instance is more likely to be a sample for which *y = 0*. To achieve the optimum **ϴ**, the loss function is defined as an objective function called the *log loss* or *cost function*, as shown in equation (3.13).

$$J(\theta) = -\frac{1}{m}\sum_{i=1}^{m}[y^i \, log(\hat{y}^i) + (1 - y^i) log\,(1 - \hat{y}^i)] \tag{3.13}$$

The term *m* represents the number of samples used in the training set, y^i and $\hat{y}^i$ represents the label of the i^{th} sample and the predicted sample respectively.

In order to determine the optimum $\boldsymbol{\theta}$, the partial derivative of the cost function is computed. Because the cost function is a convex function, an optimization technique such as the gradient descent method, as noted by Geron, can be used to determine the global minimum (Geron, 2019).

3.3.3.3 Support Vector Machine

Support Vector Machine or (SVM) is a machine learning technique capable of classifying the trained model and understand pattern within the data for both linear and non-linear data. SVM is a powerful supervised machine learning model that allows grouping and classification using a separator and the maximum margin classification (Burman and Som, 2019). The SVM is based on a hyperplane separator that can be either line, plane, or hyperplane to separate the different classes of the training set for it to be used for the target data depending on the dimension of the represented data. SVM requires a preprocessing of the data that includes data normalization, as it is sensitive to the scale of the data. The SVM method includes different types of kernels, such as (linear, polynomial, and Gaussian radial basis function RBF). These kernels are functions that map the data into a higher dimension, which means these kernels work to increase the dimensionality of the data to make the separation/ classification easier. While using this model, a hyperparameter C also called regularization parameter is used to control the tradeoffs between the margin violation from the outliers for the soft margin classification/support vector classifier. The hyperparameter is optimized to be used to train training data while searching for the optimal hyperplane that maximizes the margin between the two groups. The accuracy and efficiency of the model are then tested using the testing data that contains new data points that were not used in the training.

The algorithm used in the SVM technique is to maximize the minimum distance between data points, as shown in Figure 3.3, where support vectors are represented by the points that lie in the boundaries (Dunham, 2009). These support vectors are the most important parameter that allows to achieve the goal of maximizing the margin.

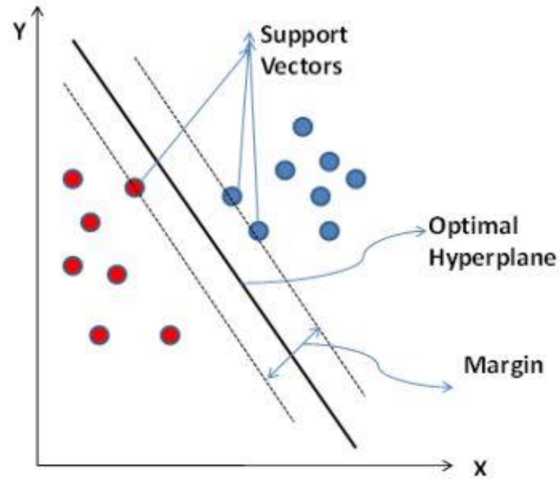

Figure 3.3 Support Machine Vector

Adapted from Vital et al. (2021)

In order to determine the optimized hyperplane of the SVM, an equation is developed, as shown in Equation (3.14), to determine $\boldsymbol{w}$ and b, where $\boldsymbol{w}$ represents the feature weight vector and b is the bias term.

$$min\ \phi(w) = \frac{1}{2}\boldsymbol{w}^T\boldsymbol{w} \qquad for\ all\ \{(x_i, y_i)\}: y_i(\boldsymbol{w}^T x_i + b) \geq 1 \tag{3.14}$$

The optimized values of $\boldsymbol{w}$ and b are used in the margin line to be used as the estimated line for the classification between the different classes (see Equation (3.15) below).

$$\boldsymbol{w}^T x + b = 0 \tag{3.15}$$

That is equivalent to maximizing the distance between the two support vectors that have the normalization.

3.3.3.4 Naïve Bayes

Naïve Bayes is a machine learning technique that allows the classification of instances using the Naïve Bayes Theorem (Brownlee, 2016). The Naïve Bayes theorem uses the observations to compute posterior probabilities (Ren et al., 2009; Liu et al., 2018). The naïve Bayes' theorem considers that the probability of the outcome depends on the probability of likelihood of evidence and the prior and is inversely proportional to the probability of the evidence, as shown in Equation (3.16) (Liu et al., 2018).

$$P(C_j|\boldsymbol{x}) = \frac{P(\boldsymbol{x}|C_j).P(C_j)}{P(\boldsymbol{x})} \tag{3.16}$$

$P(C_j \mid x)$ represents the probability of an instance $\boldsymbol{x}$ class C_j; $P(\mathbf{x}|C_j)$ represents the probability of generating instance $\boldsymbol{x}$ given class C_j; $P(\boldsymbol{x})$ represents the probability of occurring instance $\boldsymbol{x}$; and $\boldsymbol{x} = (x_1, \ldots, x_n)$.

The naïve Bayes classifier assumes that $x_i's$ are conditionally independent, given C_j, hence the following Equation (3.17) can be used:

$$\begin{aligned} P(\boldsymbol{x}|C_j) = P(x_1, x_2, \ldots, x_n|C_j) &= P(x_1|C_j) * P(x_2|x_1, C_j) * \ldots P(x_n|x_1, \ldots x_{n-1}, C_j) \\ &= P(x_1|C_j) * P(x_2|C_j) * \ldots P(x_n|C_j) \\ &= \prod_1^n P(x_i|C_j) \end{aligned} \tag{3.17}$$

The conditional independence assumption previous equation (3.17) can be used in the naïve Bayes theorem Equation (3.16) to get Equation (3.18):

$$P(C_j|\boldsymbol{x}) = \frac{P(C_j).\prod_1^n P(x_i|C_j)}{P(\boldsymbol{x})} \tag{3.18}$$

Thus, the naïve Bayes classification allows us to compute "y" using the following Equation (3.19) (Manning, 2008).

$$y = arg\max_{y} P(C_j)\prod_{1}^{n} P(x_i|C_j) \tag{3.19}$$

The naïve Bayes includes different models, namely Gaussian naïve Bayes for continuous data, Multinomial naïve Bayes for the multinomial distributed data (frequency, count data), and complement naïve Bayes that is an extension for the multinomial as it is best suited for imbalanced data, Bernoulli naïve Bayes for binary data.

3.3.3.5 Decision Tree

Decision tree is a machine learning algorithm that can be used not only for classification and regression purposes but also for multioutput purposes. Decision trees are considered to be powerful as they permit to fit even complex datasets (Geron, 2022). It is easy to interpret because decision trees can be visualized and require little data preparation (Geron, 2022). The algorithm is built using recursive partitioning to classify the data and chooses the most predictive features to split the data and build a tree-like model (Liu et al., 2017; Fan et al., 2006). The algorithm for building the model is as follows:

- Chooses an attribute/feature from the dataset
- Computes the significance of attributes in splitting data
- Split the data based on the value of the best attribute
- Then go back to the first step to repeat for all attributes.

In the tree, each internal node represents a test, each branch represents a test result, and the leaf represents a class. The classification of the new data point starts from the decision node/root node to then traverses down the tree based on the feature tests until it reaches the leaf. The goal of the decision tree is to build a model that maximizes the predictive power of new data points while having the lowest possible impurity and entropy. Therefore, decision trees focus on determining the best attributes to use as a classifier using different measures such as impurity Gini index, entropy, and chi-square (Alzubi et al., 2018). The impurity of the node is defined in the following manner: a node is said to be pure, G = 0, when the node contains one class only Equation (3.20). On the other hand, entropy is defined by the amount of information disorder or randomness in the data Equation (3.21).

$$G_i = 1 - \sum_{k=1}^{n} p_{ik}^2 \tag{3.20}$$

where p_{ik} is the ratio of class *k*.

$$H_i = - \sum_{\substack{k=1 \\ p_i, k \neq 0}}^{n} log_2(p_{i,k}) \tag{3.21}$$

There exist different algorithms to implement and train the decision trees. One of these classification algorithms is Classification and Regression (CART), which splits trees to contain only two children for each parent (binary), Iterative Dischomiser 3 (ID3), Automatic Interaction Detection (CHAID), and many other Chi-squared algorithms (Alzubi et al., 2018). This presented dissertation relies on using the Sckit-Learn package, which uses the CART algorithm. The CART algorithm divides the node that refers to a feature *k* into two nodes using a threshold t_k (Geron, 2022). In order to choose both parameters (*k*, t_k) that permit to have the purest impurity of node *i*, the Equation (3.22) is used (Geron, 2022). The cost function for CART, Equation (3.22), determines the optimal pair (*k*, t_k).

$$minimize\ J(k, t_k) = \frac{m_{left}}{m} G_{left} + \frac{m_{right}}{m} G_{right} \tag{3.22}$$

where G_{left} or G_{right} refers to the impurity of the left/right split; and m_{left} or m_{right}refers to the instances in the left/right split. The splitting process is repeated for each children node recursively until the value of the maximum depth is reached (Geron, 2022). Since the CART algorithm is a binary one that demands $O(\log_2(m))$ nodes to be checked, which is equivalent to one feature for each node.

The decision trees are powerful because they can be used for different purposes, as noted previously but also handle different categories. As the scope of this proposed dissertation aims to predict the class of new students, only the classification function of the decision tree will be used.

3.3.3.6 Ensemble learning

The word "ensemble learning" refers to a group of predictors combined in a supervised machine-learning technique in order to reach a better decision or prediction. The combined predictor of ensemble learning can be a regressor or classifier model. It can be of any technique like a decision tree, logistic regression, and the like. The fundamental concept of ensemble learning is that through the combination of multiple models/ techniques, the errors of one model will most likely be compensated by other models, which will eventually improve the performance of the ensembled model compared to each model alone (Sagi and Rokach, 2018). Hence, the ensemble methods permit to improve the robustness and accuracy of the model. According to Dietterich (2002), ensemble learning permit to obtain a better performance because it overcomes three main problems faced by individual models. The first issue deals with the statistical problem that is due to the search space of the hypotheses that can be too large relative to the training set. In the situation in which different hypotheses are developed that may have similar accuracy on the training set but may not produce the same accuracy in the testing set when chosen (Dietterich, 2002). However, ensemble learning can overcome the problem by simply voting on the most frequently predicted class by these equally-good classifiers. The second issue deals with the computational problem that is due to the inability of the model to find the optimum hypothesis within the hypothesis space (Dietterich, 2002). Ensemble learning permits the algorithm to not get trapped in a local minima using a weighted combination of different local minima. The third and last issue concerns the representational problem, which often arises when no hypotheses within the hypothesis space provide an accurate approximation of the function f (Dietterich, 2002). The ensemble learning uses the weighted vote of the hypotheses to construct a more appropriate and close function f. Additionally, Polikar (2006) has listed the reasons behind which ensemble learning is preferable to use. According to his research, statistical reasons, large volumes of data, too little data, divide and conquer, and data fusion are all the reasons why ensemble learning works (Polikar, 2006).

There are three commonly used methods of ensemble learning, which rule the field of ensemble learning, although there are many possible combinations that can be used (Brownlee, 2021, Geron, 2019). The three most popular techniques are bagging, boosting, and stacking. Another method category that is used in different studies in the literature is random forest. For example, the study by Uzel et al. (2018) used random forests and voting classifiers, among other machine learning models, to study the success of students from primary, secondary, and high school. In a recent study, Aldrees and his colleague investigated the possibility of building predictive models for water pollution using ensemble learning and random forest (Aldrees et al., 2023). In order to study the cancer prognosis and diagnosis, Zolfaghari et al. (2023) used different machine learning techniques such as Naïve Bayes and SVM, but also used Bagging and boosting models.

In this proposed dissertation, three different ensembled learning models are used, namely Voting Classifier, Bagging, and Random Forest which are described in the following sectors.

3.3.3.6.1 Voting Classifier

The fundamental idea of the voting classifier is to integrate the prediction of all the used classifiers, and the predictions are made based on the majority of all involved models (Brownlee, 2020). The voting techniques can be applied in either a weighted manner or an unweighted manner (Uzel et al., 2018). As listed in the research by Moreno et al., 2006, the unweighted technique is used when all used classifiers are of equal importance. In the unweighted method, the data instance is determined based on the ones with the highest vote. On the other hand, for the weighted method, the used classifiers are of different importance. In the weighted method, the data instance can be determined using different techniques, i.e., simple weighted vote, re-scaled weighted vote, best-worst weighted vote, and quadratic best-worst vote (Moreno et al., 2006).

The majority vote prediction for voting classification can be made following two approaches. The first approach is hard voting, which determines the class label based on summing all predictions for each class and choosing the one with the most votes (Geron, 2019). The second approach is soft voting, which consists of predicting the class label with the highest probability by summing the predicted probabilities (Brownlee, 2020).

3.3.3.6.2 Bagging

Bootstrap aggregating or bagging is a simple and effective ensemble learning method (Polikar, 2006; Sagi and Rokach, 2018, Geron, 2019). As part of the bagging, different classifier methods of the same type are trained using different subsets of bootstrapped replicas of the training data (Polikar, 2006). These subsets are chosen at random from the entire training set with replacements. Each classifier will make its own prediction on its respective subset of the training set, which is then combined with other classifiers' predictions by majority vote.

As mentioned above, the sampling for bagging is with replacement, there is a likelihood that some data points from the original training data are selected more than once while some others may not be selected at all. The possibility of a data point appearing multiple times in different subsets increases the overlapping possibility. In this case, an unstable model will permit to include diversity and improve the model's accuracy since it generates different decision boundaries for small perturbations in the training data. Two good candidate models for this purpose are decision trees and neural networks (Polikar, 2006). According to Sagi and Rokach (2018), bagging is the second most used ensemble learning method, it is applied in more research papers compared to AdaBoost and Gradient boosting.

3.3.3.6.3 Random Forest

Random Forest is another ensemble learning method that has been used extensively in the literature because it easy to use in different problems while providing high accuracy (Biau and Scornet, 2016; Belgiu and Dragut, 2016). It is the first most used method compared to bagging, AdaBoost, and gradient descent in 2016, according to Sagi and Rokach (2018). Random forest is a method introduced by Amit and German (1997) and Ho (1998) around the same period, which was then further elaborated by Dietterich in 2000. Random Forest classifier is created from an ensemble of decision trees. The Random Forest classifier uses the same approach of bagging since it samples different subsamples with replacement. The subsamples contain the same number of data points available in the original training set. Each decision tree is built using a different subset with a randomly selected feature set. The Random Forest algorithm works in such a manner to include randomness to grow the random tree while searching for the best subset of features (Geron, 2019). This Random Forest tree permits to build of a collection of trees that are of different features, which permits to ensure less sensitivity to the training data.

3.3.3.7 Evaluation measures

In order to evaluate the performance of models, different measuring features need to be checked. According to Oslon and Delen (2008), there exist three main measuring features that are commonly used in the literature, i.e., accuracy, precision, and recall. The first metric, accuracy, measures the percentage for which the testing data is correctly predicted, as provided in Equation (3.23). The second metric, precision, measures the percentage to obtain the same results repeatedly under the same conditions as provided in Equation (3.24). The last metric, recall, measures the ratio of true positives with respect to all positive instances (true positives and false negatives), as shown in Equation (3.25). In the research article of Uzel et al. (2018), they add the F-measure or F1, which is related to both the precision and the recall and is simply their harmonic mean as provided in Equation (3.26).

$$Accuracy = \frac{TP + TN}{TP + TN + FN + FP} \tag{3.23}$$

$$Precision = \frac{TP}{TP + FP} \tag{3.24}$$

$$Recall = \frac{TP}{TP + FN} \tag{3.25}$$

$$F1 = \frac{2 * precision * recall}{precision + recall} \tag{3.26}$$

CHAPTER IV

RESULTS AND DISCUSSION

4.1 Analytic Hierarchy Process

AHP was used to determine students' preference of ST view either systemic/holistic or less systemic/reductionist to deal with complex system. Using the ST dimensions from Jaradat (2015) as the criteria and defining the alternatives as reductionist or holistic, the proposed AHP model is provided in Table 4.1. From here, the pairwise comparison process can be completed based on the diagram in Figure 4.1.

Table 4.1 Key parameters and indicators used to evaluate students' preference

Criteria		Alternatives
Level of Complexity	1 Simplicity (S)	Reductionist
	2 Complexity (C)	Holistic
Level of Independence	1 Autonomy (A)	Reductionist
	2 Integration (G)	Holistic
Level of Interaction	1 Isolation (N)	Reductionist
	2 Interconnectivity (I)	Holistic
Level of Change	1 Resistance to change (V)	Reductionist
	2 Tolerance to change (Y)	Holistic
Level of Uncertainty	1 Stability (T)	Reductionist
	2 Emergence (E)	Holistic
Level of Systems worldview	1 Reductionist (R)	Reductionist
	2 Holistic (H)	Holistic
Level of Flexibility	1 Rigidity (D)	Reductionist
	2 Flexibility (F)	Holistic

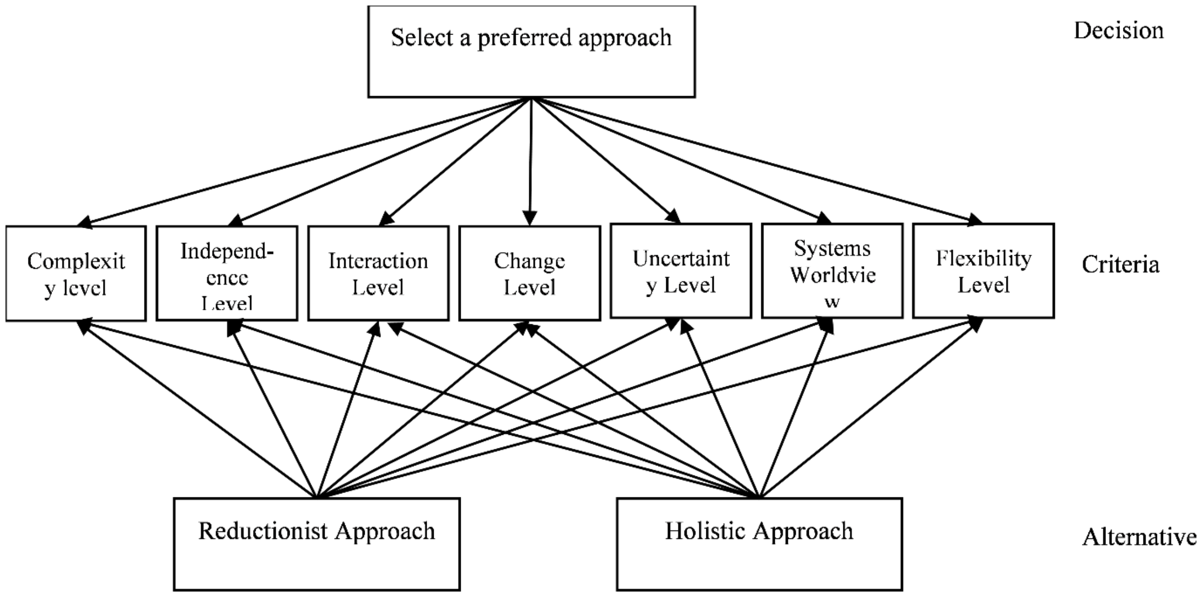

Figure 4.1 AHP Hierarchy structure of the problem

Since there are 7 criteria, a 7×7 pairwise comparison matrix, A, was created. Each entry in the matrix, x_{ij}, refers to the entry in row i and column j of the comparison matrix. An example of a student's entry permit to fill the matrix A as follows in Equation 4.1. The first row provides information about the preference of the student concerning the level of complexity with respect to the other six remaining criteria. For instance, this student rated the level of complexity to be less important than the six levels. The student rated the level of change and flexibility to be of absolute importance compared to the level of complexity as reflected in the attributed scale of "1/9". Similarly, the student rated the level of independence and uncertainty to be essentially or strongly important to the level of complexity as reflected by the attributed scale of "1/5".

$$
A = \begin{array}{cccccccc}
Criteria & Complexity & Independence & Interaction & Change & uncertainty & worldview & Flexibility \\
Complexity & 1 & 1/5 & 1/7 & 1/9 & 1/5 & 1/3 & 1/9 \\
Independence & 0.20 & 1 & 1/5 & 1/7 & 1/5 & 1/3 & 1/9 \\
Interaction & 1 & 0.20 & 1 & 1/5 & 1/7 & 1/3 & 1/9 \\
Change & 0.11 & 0.33 & 0.14 & 1 & 7 & 5 & 1 \\
Uncertainty & 0.11 & 0.20 & 0.14 & 0.33 & 1 & 5 & 1/5 \\
Worldview & 1 & 1 & 1 & 7 & 9 & 1 & 1 \\
Flexibility & 0.33 & 0.33 & 0.20 & 3 & 3 & 0.33 & 1
\end{array} \quad (4.1)
$$

The next step is to normalize the matrix by dividing each entry in a specific column by the sum of the entries in that specific column. The sum of the columns is presented in the following Equation 4.2.

$$
Total = \begin{array}{ccccccc}
complexity & Independence & Interaction & Change & Uncertainty & Worldview & Flexibility \\
39.00 & 30.20 & 25.34 & 2.80 & 13.74 & 13.00 & 3.53
\end{array} \quad (4.2)
$$

The normalized pairwise comparison matrix is computed using the resulted sum in Equation 4.2, as presented in Equation 4.3. The sum of each column is 1 since the elements of the matrix are normalized.

$$
A_{norm} = \begin{array}{cccccccc}
Criteria & Complexity & Independence & Interaction & Change & uncertainty & worldview & Flexibility \\
Complexity & 0.0256 & 0.0066 & 0.0056 & 0.0397 & 0.0146 & 0.0256 & 0.0314 \\
Independence & 0.1282 & 0.0331 & 0.0079 & 0.0511 & 0.0146 & 0.0256 & 0.0314 \\
Integration & 0.1795 & 0.1656 & 0.0395 & 0.0715 & 0.0104 & 0.0256 & 0.0314 \\
Change & 0.2308 & 0.2318 & 0.1973 & 0.3575 & 0.5094 & 0.3846 & 0.2830 \\
Uncertainty & 0.1282 & 0.1656 & 0.2762 & 0.0511 & 0.0728 & 0.3846 & 0.0566 \\
Worldview & 0.0769 & 0.0993 & 0.1184 & 0.0715 & 0.0146 & 0.0769 & 0.2830 \\
Flexibility & 0.2308 & 0.2980 & 0.3551 & 0.3575 & 0.3638 & 0.0769 & 0.2830
\end{array} \quad (4.3)
$$

In order to determine the weight of each dimension, an average of each row is computed from the normalized matrix. The following results are obtained, as represented bellow in 4.4:

$$W_{complexity} 0.0213 =; W_{independence} = 0.0417; W_{interaction} = 0.0748;$$
$$W_{change} = 0.3135; W_{uncertainty} = 0.1621; W_{worldview} = 0.1058; \tag{4.4}$$
$$W_{flexbility} = 0.2807$$

The next step consists of computing the consistency ratio. The consistency ratio is checked using the consistency index and random consistency index for n=7 as shown in Table 3.4 and found that the pairwise comparison doesn't provide any serious inconsistency.

Using the results in Equation 4.4, priority values, the student ranks the dimensions from more important to less important to be: 1. The level of change, 2. The level of flexibility, 3. The level of uncertainty 4. The level of systems worldview, 5. The level of interaction, 6. The level of independence, 7. The level of complexity.

Now that the pairwise comparison is established between the criteria, the pairwise comparison needs to be determined for the alternatives. For example, in the level of complexity the student determined the following scales, which permit to construct the following matrix in Equation 4.5 and the normalized matrix in Equation 4.6:

$$A = \begin{array}{ccc} \textit{In the level of Complexity} & \textit{Simplicity} & \textit{Complexity} \\ \textit{Simplicity} & 1 & 7 \\ \textit{Complexity} & 0.14 & 1 \end{array} \tag{4.5}$$

$$A_{norm} = \begin{array}{c} \textit{Simplicity} \\ \textit{Complexity} \end{array} \begin{bmatrix} 0.875 & 0.125 \\ 0.125 & 0.875 \end{bmatrix} \tag{4.6}$$

Because the simplicity refers to the reductionist and complexity refers to holistic, the above yields to the following priority vector for the complexity Equation 4.7:

$$Reductionist_{complexity} = 0.875; Holistic_{Complexity} = 0.125 \quad (4.7)$$

The following Table 4.2 provide a summary of the findings of the weighted values of the two alternatives for each dimension.

Table 4.2 The weighted value of all the levels

Dimension	Reductionist	Holistic
Level of Complexity	0.875	0.125
Level of Independence	0.125	0.825
Level of Interaction	0.250	0.750
Level of Change	0.100	0.900
Level of Uncertainty	0.166	0.833
Level of Systems Worldview	0.166	0.833
Level of Flexibility	0.125	0.825

The last step of the AHP consists of determining the overall score in order to determine the overall ranking/ score for the alternatives. Using the above calculations and Table 4.3, the student's final ranking of the alternatives is 0.1536 or 15.36% for reductionist and 0.8463 or 84.63% for holistic. In this case, the student prefers the holistic view of ST over the reductionist.

Table 4.3 Overall score calculation

	Score Calculation	Overall Score
Reductionist	0.0213*0.875+0.0417*0.125+0.0748*0.25+0.3135*0.1+ 0.1621*0.166+0.1058*0.166+0.2807*0.125	0.1536
Holistic	0.0213*0.125+0.0417*0.825+0.0748*0.750+0.3135*0.9+ 0.1621*0.833+0.1058*0.833+0.2807*0.825	0.8463

The study aims to determine the preference to ST approaches of the students based on their demographic factors and to check the significance of each factor on their ranking, for this reason, the overall preferences are kept independent. Therefore, the above result only represents the preference of one student. The exact procedure was completed for all 372 participants.

4.1.1 Overall students' preference using AHP

This section aims to provide an overview of the aggregated weight of the students' judgment about the seven dimensions (complexity, independence, interaction, change, uncertainty, systems worldview, and flexibility), and the overall ST approach (reductionist and holistic views). The aggregated method is based on the arithmetic mean for all the subsections (Yap et al., 2019; Liu et al., 2020). The aggregated result of the students' judgments concerning ST is shown in Figure 4.2.

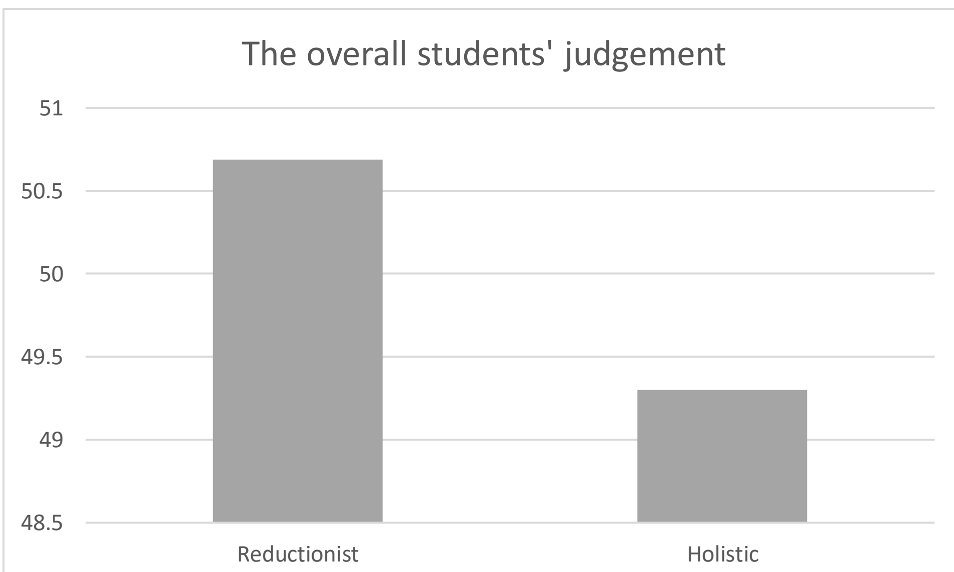

Figure 4.2 The overall students' preference of ST dimensions and approach using AHP (n=372)

Figure 4.3 and figure 4.4 provide more detail on the students' total aggregate ST reductionist and holistic preference. The total reductionist preference of the 372 students in the sample of the population is a mean of 50.68% with a standard deviation of 17.55. On the other hand, the overall holistic preference of the 372 students in the sample population is 49.29%.

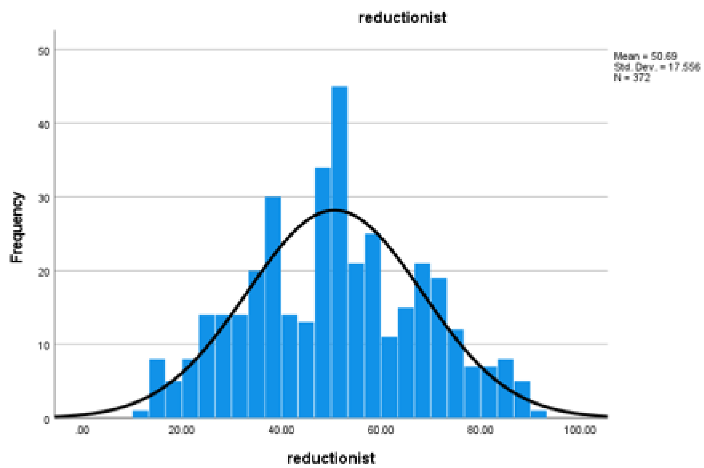

Figure 4.3 Frequency distribution of the total aggregate ST reductionist approach preference of the students (n=372)

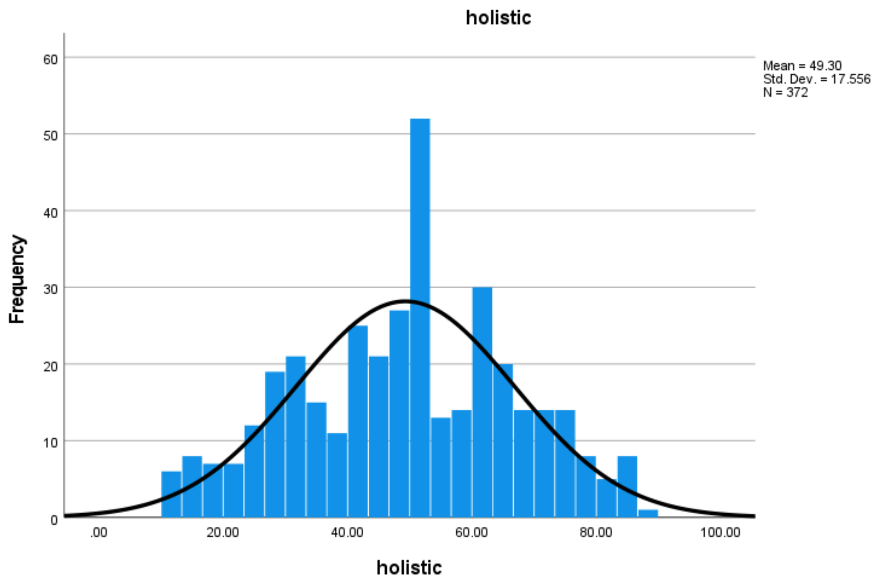

Figure 4.4 Frequency distribution of the total aggregate ST holistic approach preference of the students (n=372)

4.2 Fuzzy Analytical Hierarchy Process

AHP has been extensively used in the literature across different fields for decision-making purposes. Because the AHP decision technique includes the decision maker's subjective judgment, the impreciseness of the decision maker can increase (Marufuzzaman et al., 2009). For this reason, the fuzzy decision-making method is applied to validate the results obtained from the AHP. Following the procedure described in the methodology section, the Fuzzy AHP is performed.

The first step of Fuzzy AHP is similar to the AHP method, which consists of defining the problem including the main goal, criteria, and alternatives. Table 4.1 illustrates the hierarchical structure of the problem and Table 4.1 describes the criteria and alternatives used in the study.

After building the hierarchical structure and determining the key parameters, the comparison matrix is constructed. Since the Fuzzy AHP includes a triangular fuzzy scale number, as presented in Table 3.5, each element in the 7*7 matrix consists of three numbers. An example of a student's entry is used to fill the comparison matrix shown in Equation 4.8.

$$\tilde{A} =$$

$$\begin{array}{r} complexity \\ indpendence \\ interaction \\ change \\ uncertainty \\ worldview \\ flexibility \end{array} \left[\begin{array}{ccccccccccccccccccccc} 1 & 1 & 1 & \frac{1}{6} & \frac{1}{5} & \frac{1}{4} & \frac{1}{8} & \frac{1}{7} & \frac{1}{6} & \frac{1}{9} & \frac{1}{9} & \frac{1}{9} & \frac{1}{6} & \frac{1}{5} & \frac{1}{4} & \frac{1}{4} & \frac{1}{3} & \frac{1}{2} & \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \\ 4 & 5 & 6 & 1 & 1 & 1 & \frac{1}{6} & \frac{1}{5} & \frac{1}{4} & \frac{1}{8} & \frac{1}{7} & \frac{1}{6} & \frac{1}{6} & \frac{1}{5} & \frac{1}{4} & \frac{1}{4} & \frac{1}{3} & \frac{1}{2} & \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \\ 6 & 7 & 8 & 4 & 5 & 6 & 1 & 1 & 1 & \frac{1}{6} & \frac{1}{5} & \frac{1}{4} & \frac{1}{8} & \frac{1}{7} & \frac{1}{6} & \frac{1}{4} & \frac{1}{3} & \frac{1}{2} & \frac{1}{9} & \frac{1}{9} & \frac{1}{9} \\ 9 & 9 & 9 & 6 & 7 & 8 & 4 & 5 & 6 & 1 & 1 & 1 & 6 & 7 & 8 & 4 & 5 & 6 & 1 & 1 & 1 \\ 4 & 5 & 6 & 4 & 5 & 6 & 6 & 7 & 8 & \frac{1}{8} & \frac{1}{7} & \frac{1}{6} & 1 & 1 & 1 & 4 & 5 & 6 & \frac{1}{6} & \frac{1}{5} & \frac{1}{4} \\ 2 & 3 & 4 & 2 & 3 & 4 & 2 & 3 & 4 & \frac{1}{6} & \frac{1}{5} & \frac{1}{4} & \frac{1}{6} & \frac{1}{5} & \frac{1}{4} & 1 & 1 & 1 & 1 & 1 & 1 \\ 9 & 9 & 9 & 9 & 9 & 9 & 9 & 9 & 9 & 9 & 9 & 9 & 1 & 1 & 1 & 4 & 5 & 6 & 1 & 1 & 1 \end{array} \right] \quad (4.8)$$

The next step of Fuzzy AHP requires the computation of the geometric mean of each criterion (complexity, independence, interaction, change, uncertainty, systems worldview, flexibility). The result of the geometric mean determined using Equation (3.6) for each criterion can be found in the following Table 4.4.

Table 4.4 The geometric mean

Criterion	**Geometric mean**		
Level of complexity	0.195	0.218	0.252
Level of independence	0.325	0.376	0.445
Level of interaction	0.543	0.624	0.731
Level of change	3.394	3.739	4.137
Level of uncertainty	1.346	1.584	1.842
Level of systems worldview	0.807	1.011	1.219
Level of flexibility	3.126	3.227	3.312
Total	9.735	10.82	11.94
Inverse	0.103	0.092	0.084
Ordered inverse	0.084	0.092	0.103

To compute the fuzzy weight $\widetilde{w_i}$ of each criterion, Equation 3.7 is used. The result of the fuzzy weights for the criteria can be found in Table 4.5.

Table 4.5 Fuzzy weights

Criterion	Fuzzy weights		
Level of complexity	0.016	0.020	0.026
Level of independence	0.027	0.035	0.046
Level of interaction	0.045	0.058	0.075
Level of change	0.284	0.349	0.425
Level of uncertainty	0.113	0.146	0.189
Level of systems worldview	0.068	0.093	0.125
Level of flexibility	0.262	0.298	0.340

The center of area method is used to de-fuzzify the fuzzy weights to obtain the weights. Equations 3.8 and Equation 3.9 are used to obtain the normalized non-fuzzy weights as shown in Equation 4.9.

$$\begin{gathered} N_{Complexity} = 0.0205, N_{Independence} = 0.0354, N_{Interaction} = 0.0585, \\ N_{Change} = 0.3480, N_{Uncertainty} = 0.1473, N_{Worldview} = 0.0940, \\ N_{Flexibility} = 0.2959 \end{gathered} \tag{4.9}$$

Using the results obtained in Equation 4.9, the priority scores obtained from the student's judgment are used to rank the dimension from most important (1) to least important (7): 1. The level of change, 2. The level of flexibility, 3. The level of uncertainty, 4. The level of systems worldview, 5. The level of interaction, 6. The level of independence, 7. The level of complexity.

Now that the pairwise comparison and criteria ranking are determined, the pairwise comparison between the alternatives needs to be constructed. For instance, following the students' attributed scales for the level of complexity, the following matrix is built Equation 4.10.

$$\tilde{A} = \begin{array}{c} simplicity \\ complexity \end{array} \begin{bmatrix} 1 & 1 & 1 & 6 & 7 & 8 \\ \frac{1}{8} & \frac{1}{7} & \frac{1}{6} & 1 & 1 & 1 \end{bmatrix} \tag{4.10}$$

Following the previously described steps, the geometric mean, fuzzy weights, and normalize non-fuzzy weights are determined for the alternatives as described in Table 4.6. Table 4.6 provides the geometric mean for the alternatives within each criterion simplicity and complexity.

Table 4.6 The geometric mean of the alternatives

	Geometric mean		
Simplicity	2.449	2.646	2.828
complexity	0.354	0.378	0.408
Total	2.803	3.024	3.237
Inverse	0.357	0.331	0.309
Ordered inverse	0.309	0.331	0.357

Equation 3.8 and Equation 3.9 are used to determine the non-fuzzy weights for the alternatives. The results of the non-fuzzy priority for the alternatives for the complexity level are presented in 4.11. The results reveal that the students prefer the simplicity (reductionist) approach over complexity (holistic) approach in the level of complexity.

$$N_{Simplicity} = 0.8742, N_{complexity} = 0.1257 \tag{4.11}$$

The same steps are followed to determine the weights for the other levels of the seven dimensions that are presented in Table 4.7. Table 4.7 determines the weights obtained in Equation 4.9 along with the non-fuzzy priority for the alternatives for each dimension. Finally, Table 4.8 presents the final weighted values of all the seven levels.

Table 4.7 The value of the criteria and alternatives

	Weights	Reductionist	Holistic
The level of complexity	0.0205	0.8742	0.1257
The level of independence	0.0354	0.1257	0.8742
The level of interaction	0.0585	0.2576	0.7423
The level of change	0.3480	0.1	0.9
The level of uncertainty	0.1473	0.1685	0.8314
The level of systems worldview	0.0940	0.1685	0.8314
The level of flexibility	0.2959	0.1257	0.8742

Table 4.8 Overall score weights for the reductionist and holistic ST approaches

	Score calculation	Overall Score
Reductionist approach	0.0205*0.8742+0.0354*0.1257+0.0585*0.2576+ 0.3480*0.1+0.1473*0.1685+0.0940*0.1685+ 0.2959*0.1257	0.1502
Holistic approach	0.0205*0.1257+0.0354*0.8742+0.0585*0.7423+ 0.1*0.9+ 0.1473*0.8314+0.0940*0.8314+ 0.2959*0.8742	0.8497

From the above calculations and Table 4.8, the student's final ranking of the alternatives are 0.1502 or 15.02% for reductionist and 0.8497 or 84.97% for holistic. In this case, the student prefers the holistic view of ST to the reductionist view. Comparing the results from AHP and Fuzzy AHP for this example student, both methods provided the same preference. Therefore, we can conclude that our results are correct and consistent because the fuzzy AHP supports the previous results of AHP.

4.2.1 Overall students' preference using Fuzzy AHP

This section provides the overall aggregate priority ranking and most preferred approach based on the judgment of the entire student population (n=372). The aggregate method is based on the arithmetic mean (Yap et al., 2019; Liu et al., 2020). The aggregated result of the students' judgments concerning ST is shown in Figure 4.5. The overall preference of the students towards the ST approach is 50.41% reductionist and 49.58% holistic. The results are similar to the previously obtained outcome from AHP analysis.

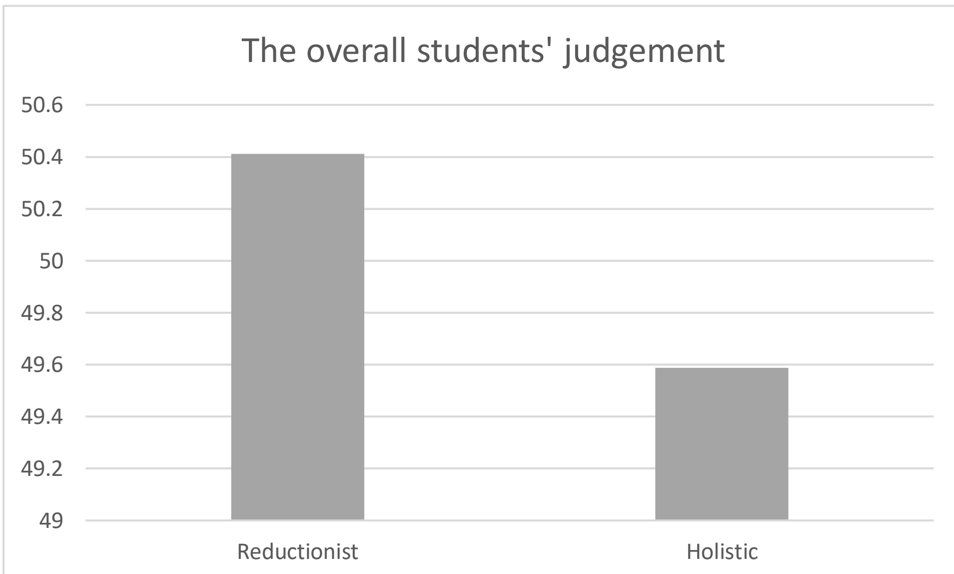

Figure 4.5 The overall students' preference of ST approach using Fuzzy AHP (n=372)

Figure 4.6 and Figure 4.7 provide more detail on the students' total aggregate ST reductionist and holistic preference. The average reductionist preference for the 372 students in the overall sample population is 50.41% with a standard deviation of 18.15. On the other hand, the average holistic preference for the 372 students in the sample population is 49.58% with a standard deviation of 18.15.

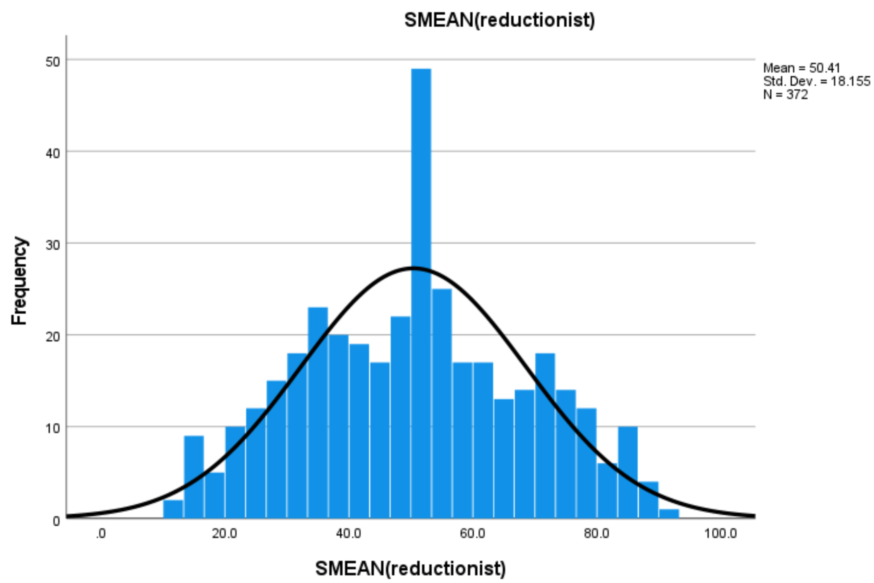

Figure 4.6 Frequency distribution of the total aggregate ST reductionist approach of the students using Fuzzy AHP (n=372)

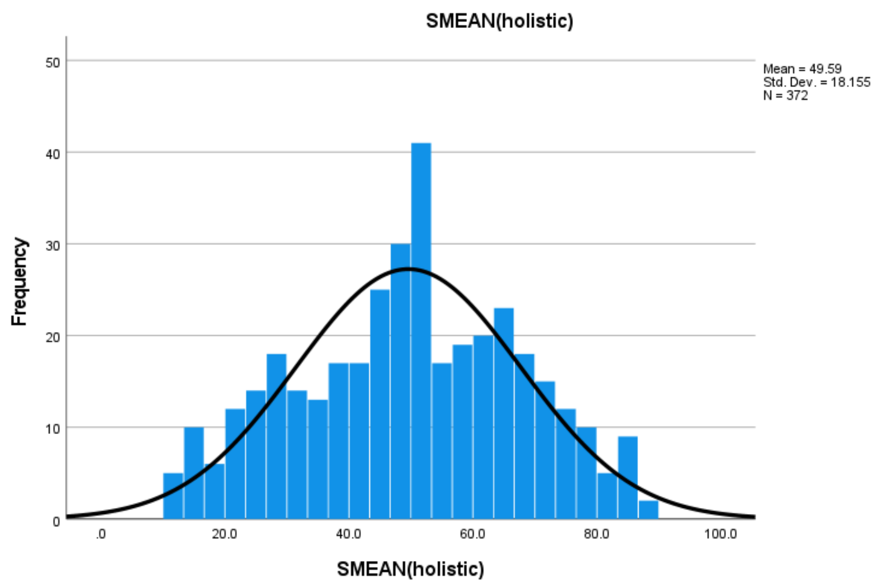

Figure 4.7 Frequency distribution of the total aggregate ST holistic approach preference of the students using Fuzzy AHP (n=372)

To determine the preferences of students for different groups, these following sections examine each group's aggregate priority ranking. The groups are determined based on the demographic and general factors: gender, learning modality, GPA, program of study, major of study, and bachelors' degree current year.

4.2.1 Aggregate students' preference of the seven dimensions

To understand the perceptions of the student towards the levels that describe ST, their aggregate ranking is investigated as shown in Figure 4.8. The ranking of the student's overall preference towards the seven dimensions was tough to decide as reflected in the overall weights. However, the judgments of the students revealed that the level of flexibility is the most favored dimension with a weight of 16.69%, followed by the of systems worldview with 15.28%. The third favorite dimension is the level of interaction at 15.18%, complexity at 14.66%, and independence at 13.72%. Lastly, the least preferred dimensions of ST are both the level of change at 12.47% and the level of uncertainty at 11.97%.

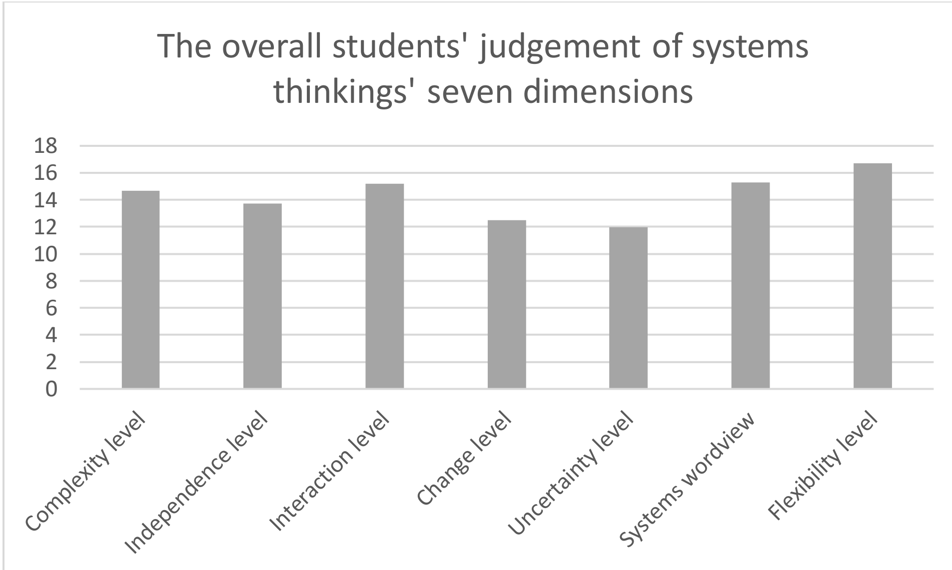

Figure 4.8 The overall students' preference of the seven dimensions using Fuzzy AHP

4.2.2 Aggregate results of the students' preference based on gender factor

Figure 4.9 represents the preference of both genders on each level of the seven dimensions of ST. Female students favor the level of flexibility at 19.34%, systems worldview 16.47%, and interaction 15.08%; followed by the level of change 12.81%, uncertainty 12.72%, complexity 11.78%, and independence 11.75%. Concerning male students, they favor the level of flexibility 15.72%, complexity 15.70%, and interaction 15.21%; followed by the level of systems worldview 14.85%, independence 14.43%, change 12.34%, and uncertainty 11.70%. Table 4.9 summarizes the ranking of the seven dimensions for both groups.

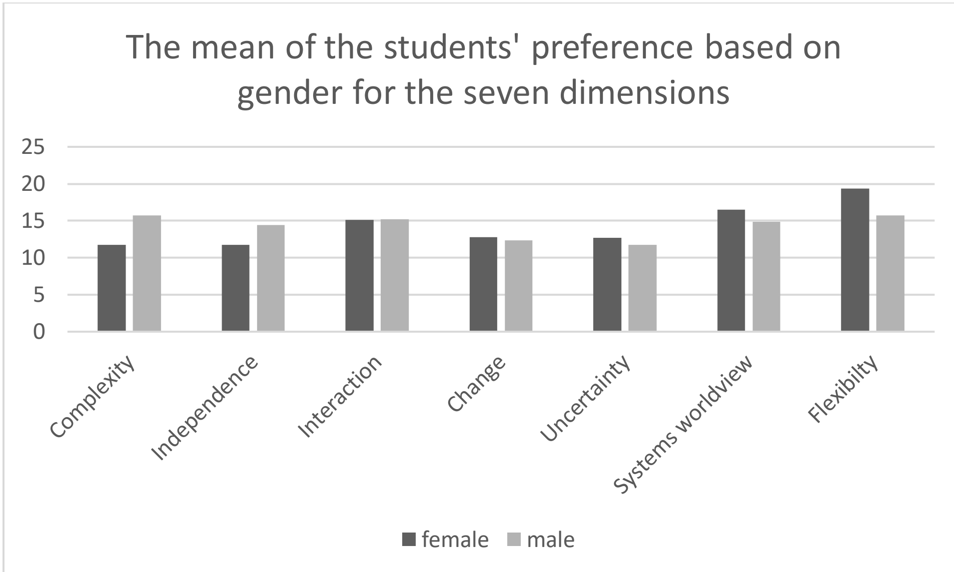

Figure 4.9 Cluster column chart for female and male students mean preference of the seven dimensions

Table 4.9 The ranking of the seven dimensions of ST for female and male students

Ranking	**Female students**	**Male students**
1	Level of flexibility	Level of flexibility
2	Level of systems worldview	Level of complexity
3	Level of interaction	Level of interaction
4	Level of change	Level of systems worldview
5	Level of uncertainty	Level of independence
6	Level of complexity	Level of change
7	Level of independence	Level of uncertainty

For the overall student's ST approach preference, female students prefer the holistic approach since the priority weight is 52.30% for holistic and 47.69% for reductionist. On the other hand, male students prefer the reductionist approach since the priority weight is 51.39% for the reductionist view and 48.60% for the holistic view. Figure 4.10 presents both female and male students overall ranking priority for the ST approach. Table 4.10 summarizes the ranking of the most preferred ST approaches for female and male students.

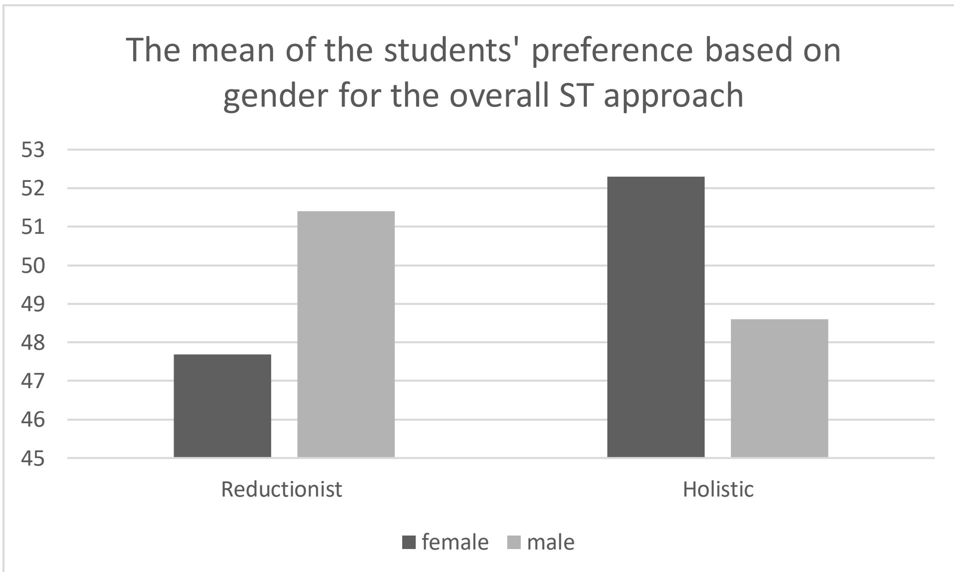

Figure 4.10 Cluster column chart for female and male students' preference of ST approach

Table 4.10 The ranking of the ST approach for female and male students

Ranking	Female students	Male students
1	Holistic approach	Reductionist approach
2	Reductionist approach	Holistic approach

4.2.3 Aggregate results of the students' preference based on the learning modality

In order to investigate the preference to ST dimensions and approached for the distance and on-campus population, the dataset was grouped based on the learning modality. Figure 4.11 presents the mean of both categories: on-campus and distance across the seven dimensions. On-campus students favor the level of flexibility 17.19%, interaction 15.10%, and systems worldview 14.99%; followed by the level of complexity 14.22%, independence 13.61, change 12.75%, uncertainty 12.11%. Distance students' most favored dimensions are the level of complexity 16.73%, systems worldview 16.63%, interaction 15.56%; followed by flexibility 14.30%, independence 14.26%, uncertainty 11.34%, and change 11.15%. Table 4.11 summarizes the ranking of the seven dimensions for both groups.

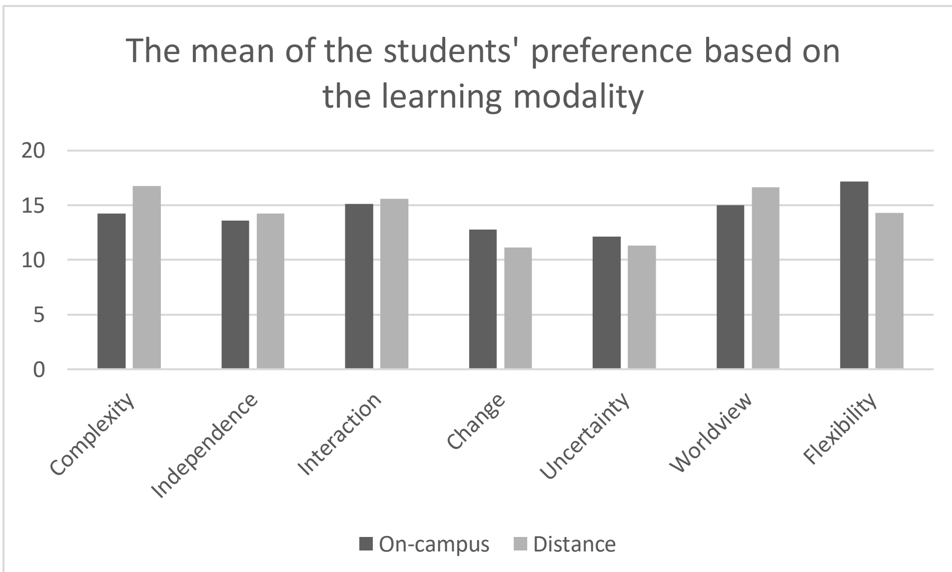

Figure 4.11 Cluster column chart for on-campus and distance students' preference of ST approach

Table 4.11 The seven dimensions ranking for the students for on-campus and distance learning modality

Ranking	On-campus students	Distance students
1	Level of flexibility	Level of complexity
2	Level of interaction	Level of systems worldview
3	Level of systems worldview	Level of interaction
4	Level of complexity	Level of flexibility
5	Level of independence	Level of independence
6	Level of change	Level of uncertainty
7	Level of uncertainty	Level of change

For the overall student's ST approach preference, both learning modality students prefer the reductionist approach over the holistic approach. On-campus students prefer the reductionist approach since the priority weight is 50.34%% compared to 49.65% for the reductionist. Distance students prefer the reductionist approach since the priority weight is 50.72%% for the reductionist and 49.27% for the holistic approach. Figure 4.12 presents both on-campus and distance students' overall ranking priority for the ST approach. Table 4.12 summarizes the ranking of the two groups' most preferred approach of ST.

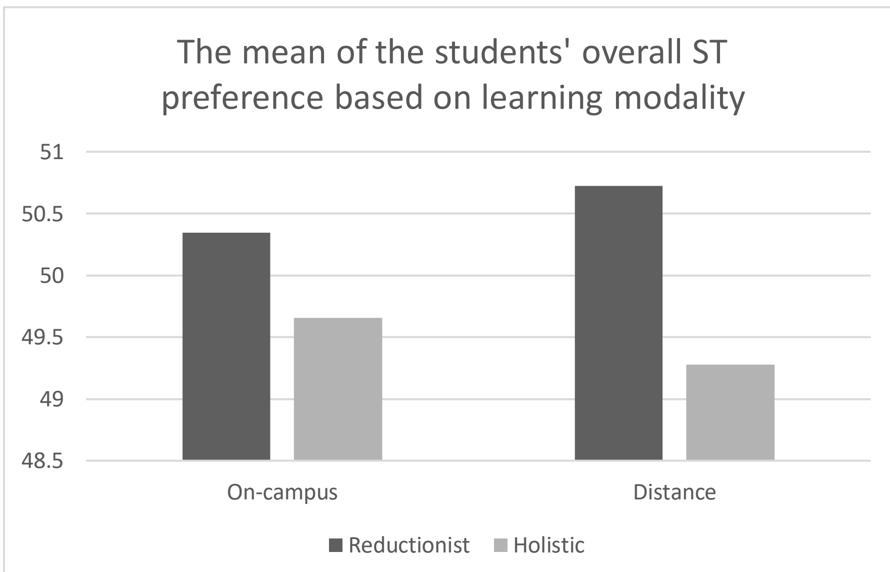

Figure 4.12 Cluster column chart for on-campus and distance students mean ST approach preference

Table 4.12 The ranking of ST preferred approach for on-campus and distance learning modality

Ranking	**On-campus students**	**Distance students**
1	Reductionist approach	Reductionist approach
2	Holistic approach	Holistic approach

4.2.4 Aggregate results of the preference of the students based on the GPA

To understand the students' preferences of each GPA group, the dataset was grouped based on the different GPA categories to check each group's aggregate ranking. Figure 4.13 illustrates the aggregate mean weight for each dimension depending on the different GPA scores. The GPA groups are GPA 4.00, 3.50-3.99, 3.00-2.49, 2.50-2.99, and 2.00-2.49 & 1.50-1.99. The last two GPAs are combined since one individual was of GPA 1.50-1.99.

The results of the fuzzy AHP reveal that the students with a GPA 4.00 favor mostly the level of flexibility 18.63%, systems worldview 18.24%, and interaction 15.32%; followed by the level of change 12.74%, independence 12.18%, uncertainty 11.44%, and complexity 11.42%. for the students with GPA 3.50-3.99, their most favored dimensions are the level of flexibility 16.89%, systems worldview 15.89%, and interaction 15.01%; followed by complexity 14.80%, independence 13.28%, uncertainty 12.07%, and change 12.03%. On the other hand, the students with GPA 3.00-3.49, the most favored dimensions are the level of complexity 16.12%, flexibility 15.41%, and interaction 15.12%; followed by the level of independence 15.05%, systems worldview 13.93, change 12.66%, and uncertainty 11.69%. Concerning the students with GPA 2.50-2.99, they favor the level of flexibility 16.93%, interaction 15.81%, and complexity 15.16%; followed by the level of systems worldview 13.96%, independence 13.14%, change 12.98%, and uncertainty 11.99%. Lastly, the group of students with GPA ranging between 1.50 and 2.49, their most preferred dimensions are the level of independence 17.96%, uncertainty 16.07%, and flexibility 14.63%; followed by the level of interaction 14.38%, complexity 13.95%, change 12.95%, and systems worldview 10.02%. Table 4.13 summarizes the ranking for the seven dimensions for different GPA groups.

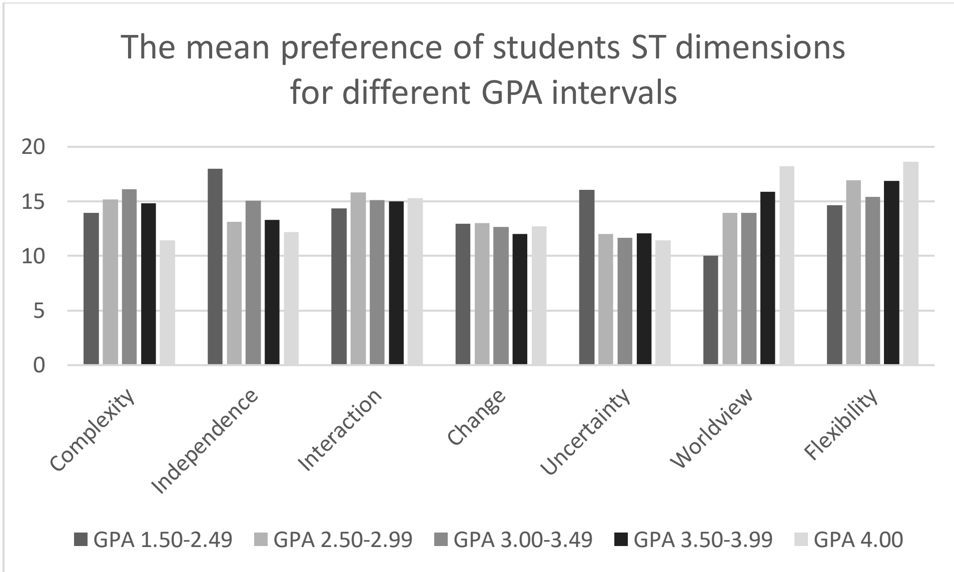

Figure 4.13 Cluster column chart for students' mean preference based on their GPA category

Table 4.13 The seven dimensions ranking for the students with different GPA

Ranking	**GPA 4.0**	**3.50-3.99**	**3.00-3.49**	**2.50-2.99**	**2.00-2.49 &1.50-1.99**
1	Level of flex[7]	Level of flex[7]	Level of Comp[1]	Level of flex[7]	Level of Indep[2]
2	Level of systems[6]	Level of systems[6]	Level of flex[7]	Level of inter[3]	Level of unc[5]
3	Level of inter[3]	Level of inter[3]	Level of inter[3]	Level of Comp[1]	Level of flex[7]
4	Level of chan[4]	Level of Comp[1]	Level of Indep[2]	Level of systems[6]	Level of inter[3]
5	Level of Indep[2]	Level of Indep[2]	Level of systems[6]	Level of Indep[2]	Level of Comp[1]
6	Level of unc[5]	Level of unc[5]	Level of chan[4]	Level of chan[4]	Level of chan[4]
7	Level of Comp[1]	Level of chan[4]	Level of unc[5]	Level of unc[5]	Level of systems[6]

*Comp[1] Complexity, *Indep[2] Independence, *inter[3] Interaction, *chan[4] Change, *unc[5] Uncertainty, *systems[6] Systems worldview, *flex[7] Flexibility.

The analysis provides students' overall preference for the two ST approaches. The result reveals that students with GPA 4.00 prefer the holistic approach of ST since the overall attributed weight is 53.43% compared to 46.56% for the reductionist approach. Similarly, the students with GPA 3.50-3.99 prefer the holistic approach because the overall ranking is 51.35% compared to 48.64% for the reductionist approach. For the students with GPA 3.00-3.49, the most preferred approach is reductionist since the overall weight is 52.89% compared to 47.10% for the holistic approach. Concerning the students with GPA 2.50-2.99 and GPA 1.50-2.49, both groups prefer the reductionist approach since the overall priority weight provided by the two groups is 53.51% and 57.41 compared to 46.48% and 46.48% for holistic respectively. Figure 4.14 and Table 4.14 summarize the preference of the ST approach for the different GPA groups.

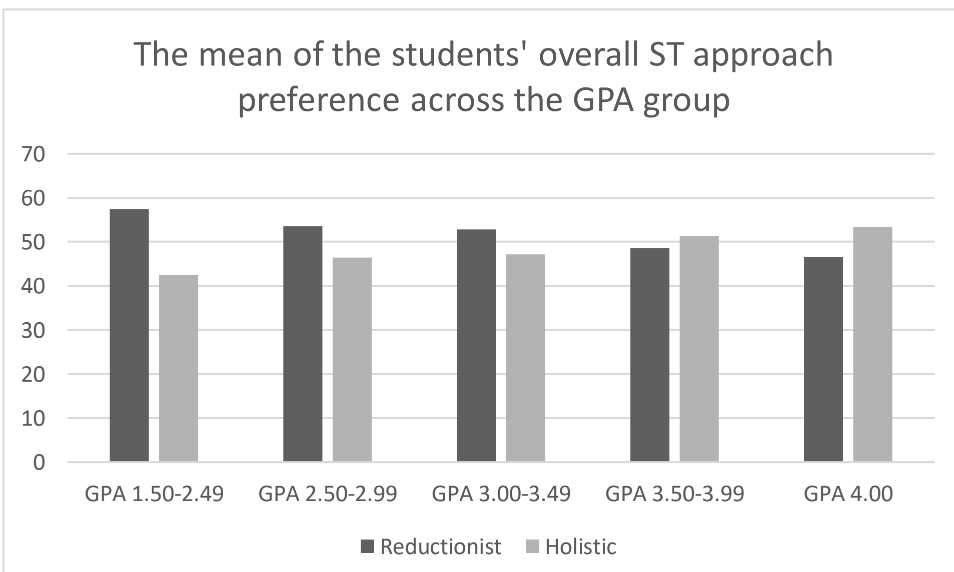

Figure 4.14 Cluster column chart for different GPA group students mean ST approach preference

Table 4.14 The ranking of students' ST most preferred approach for different GPA groups

Ranking	GPA 4.0	3.50-3.99	3.00-3.49	2.50-2.99	2.00-2.49 &1.50-1.99
1	Holistic approach	Holistic approach	Reductionist approach	Reductionist approach	Reductionist approach
2	Reductionist approach	Reductionist approach	Holistic approach	Holistic approach	Holistic approach

4.2.5 Aggregate results of the preference of the students based on the program of study

To discover the preference of the students independently based on the program of study, the dataset was grouped based on the student's current enrollment degree. The three degrees are bachelor's degree program, master's degree program, and doctoral degree program. As illustrated in Figure 4.15, the bachelor's students' mean preference reveals that the most preferred dimensions are the level of flexibility 17.34%, interaction 15.04%, and systems worldview 15.02%; followed by the level of complexity 13.98%, independence 13.54%, change 12.59%, and uncertainty 12.46%. The analysis reveals that the masters' students' most preferred dimensions are the level of complexity 17.32%, systems worldview 16.61%, and interaction 15.83%; followed by flexibility 14.40%, independence 14.23%, change 11.63%, and uncertainty 9.93%. Finally, concerning the Ph.D. students, the aggregate results show that their most preferred dimensions are the level of complexity 17.55%, independence 17.30%, and change 17.13%; followed by the level of interaction 14.09%, systems worldview 12.22%, uncertainty 11.61%, and flexibility 10.07%. Table 4.15 summarizes the seven dimensions' ranking for the three-degree program groups.

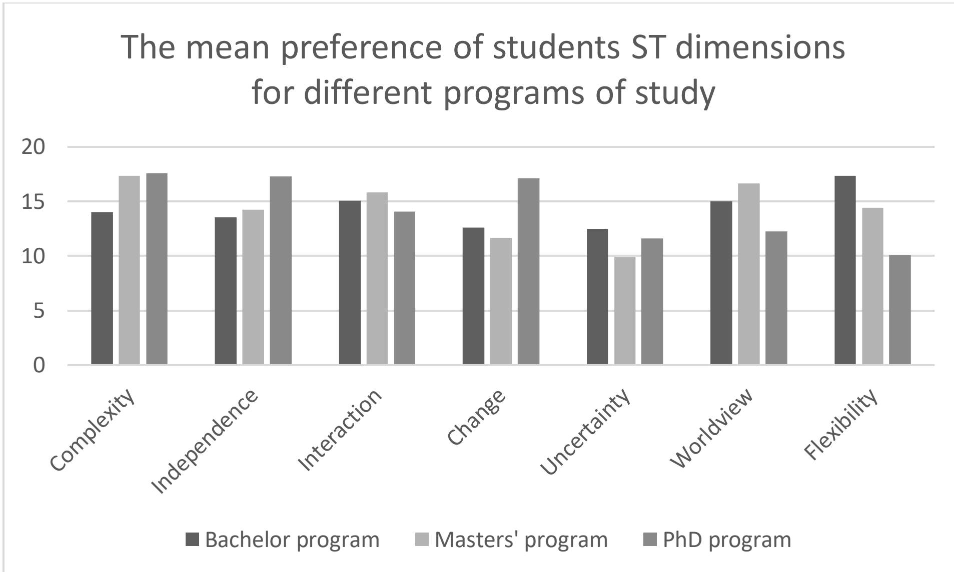

Figure 4.15 Cluster column chart for students' mean preference based on the program of study

Table 4.15 The seven dimensions ranking for students from different program degree

Ranking	Bachelor's degree	Master's degree	Doctoral degree
1	Level of flexibility	Level of complexity	Level of complexity
2	Level of interaction	Level of systems worldview	Level independence
3	Level of systems worldview	Level of interaction	Level of change
4	Level of complexity	Level of flexibility	Level of interaction
5	Level of independence	Level of independence	Level of systems worldview
6	Level of change	Level of change	Level of uncertainty
7	Level of uncertainty	Level of uncertainty	Level of flexibility

Overall, the students pursuing their bachelor's degree prefer the reductionist approach since the aggregate weight is 51.06% for the reductionist preference and 48.93% for the holistic preference. On the other hand, the students pursuing their master's degree prefer the holistic approach since the aggregate weight is 52.20% for the holistic approach and 47.79% for the reductionist approach. Lastly, Ph.D. students prefer the holistic approach since the mean weight is 51.62% for the holistic approach and 48.37% for the reductionist approach. Figure 4.16 and Table 4.16 give the preference of the ST approach for the different programs of study.

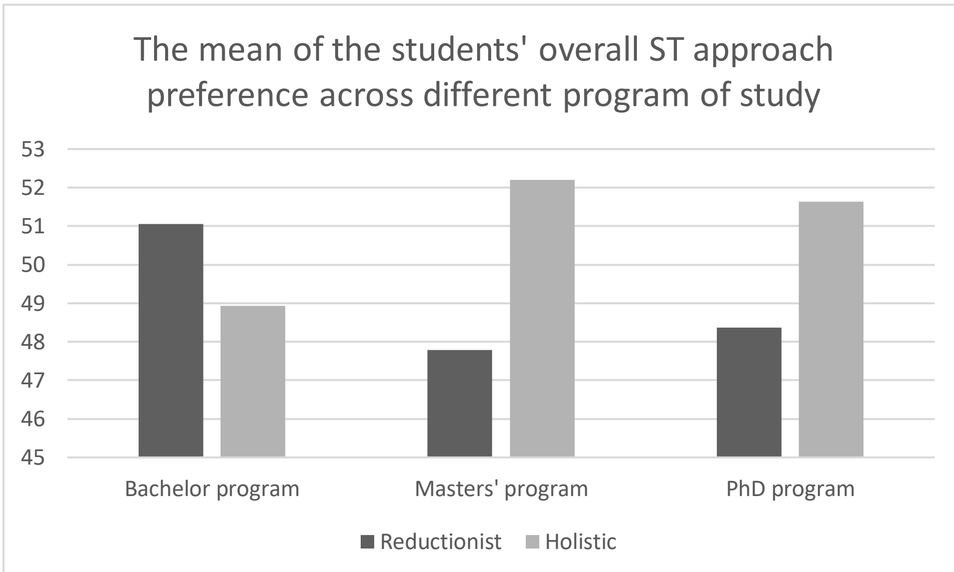

Figure 4.16 Cluster column chart for different programs of study's mean ST approach preference

Table 4.16 The ranking of the students' ST most preferred approach for different programs degree

Ranking	Bachelor's degree	Master's degree	Doctoral degree
1	Reductionist approach	Holistic approach	Holistic approach
2	Holistic approach	Reductionist approach	Reductionist approach

4.2.6 Aggregate results of the preferences of the students based on the major of study

To discover the preference of the students independently based on the field of study, the dataset was grouped based on the majors of study. The dataset is grouped based on twelve different majors of study. Figure 4.17 represents the mean score weights of the students for the seven dimensions from different majors of study. For instance, aerospace engineering students' most preferred dimensions are the level of flexibility 19.50%, interaction 17.08%, and systems worldview 15.02%; followed by the level of independence 12.99%, complexity 12.92%, and uncertainty 11.65%. Biomedical students' most preferred dimensions are the level of systems worldview 17.39%, interaction 16.48%, and uncertainty 13.67%; followed by the level of flexibility 13.45%, complexity 13.36%, change 12.81%, and independence 12.80%. For chemical engineering students, their most favored dimensions are the level of flexibility 16.70%, interaction 15.20%, and independence 15.06%; followed by the level of complexity 13.69%, change 13.69%, systems worldview 13.01%, and uncertainty 12.61%. Civil engineering students prefer the level of complexity 17.01%, interaction 15.12%, and systems worldview 14.94%; followed by the level of flexibility 14.30%, independence 14.00%, change 12.35%, and uncertainty 12.24%. Concerning computer science engineering students, their most preferred dimensions is the level of flexibility 17.91%, systems worldview 16.29%, and complexity 14.64%; followed by the level of independence 13.87%, uncertainty 12.85%, interaction 12.49%, and change 11.91%. Electrical engineering students favor the level of flexibility 19.04%, independence 15.02%, and systems worldview 14.37%; followed by the level of complexity 13.83%, interaction 13.03%, uncertainty 12.52%, and change 12.17%. For industrial and systems engineering ISE major, the students favor the level of flexibility 17.56%, systems worldview 15.34%, and interaction 15.04%; followed by the level of complexity 14.21%, change 13.15%, independence 13.05%, and uncertainty 11.61%. Concerning master business administration, MBA students, the most preferred dimensions are the level of systems worldview 16.54%, complexity 16.16%, and interaction 16.11%; followed by the level of flexibility 14.85%, independence 14.23%, change 12.23%, and uncertainty 9.85%. For mechanical engineering students' most preferred dimensions is the level of flexibility 18.84%, interaction 16.11%, and systems worldview 14.88%; followed by the level of complexity 13.99%, independence 13.00%, change 11.91%, and uncertainty 11.23%. The next group of petroleum engineering major, student favor the level of complexity 34.99%, independence 13.45%, and interaction 12.30%; followed by the level of systems worldview 11.65%, flexibility 11.65%, uncertainty 10.03%, and change 5.90%. For software engineering students, the most preferred dimensions are the level of interaction 19.41%, systems worldview 16.34%, and uncertainty 15.15%; followed by the level of flexibility 14.09%, independence 12.67%, change 12.60%, and complexity 9.70%. Lastly, for the final group that includes the students from other departments (i.e., military, MENG, educational engineering, and others), the most preferred dimensions are the level of complexity 20.59%, independence 17.18%, and systems worldview 14.73%; followed by the level of change 14.36%, uncertainty 12.30%, interaction 11.83%, and flexibility 8.99%. Table 4.17 summarizes the mean priority scores rankings of the students in different majors on the seven dimensions.

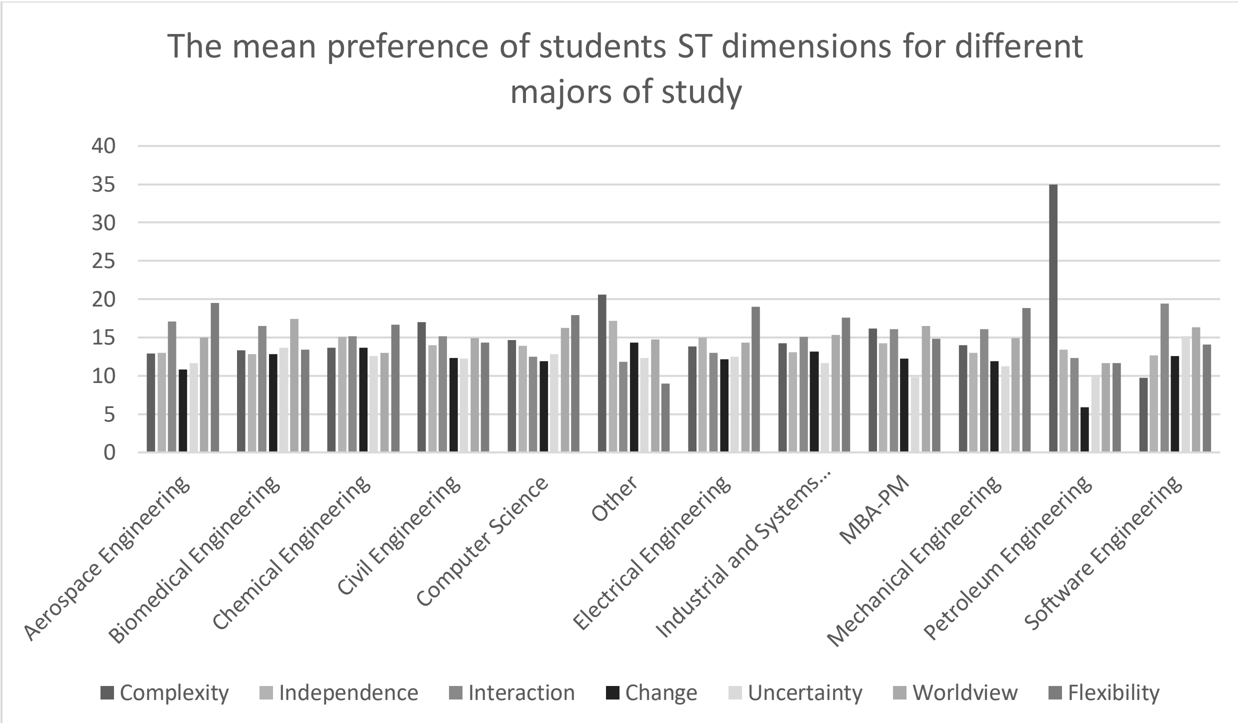

Figure 4.17 Aggregate priority results of the students from different departments

Table 4.17 The ranking of the seven dimensions across different majors of study

Majors of study	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Aerospace engineering	Level of flex[7]	Level of inter[3]	Level of systems[6]	Level of Indep[2]	Level of Comp[1]	Level of unc[5]	Level of chan[4]
Biomedical engineering	Level of systems[6]	Level of inter[3]	Level of unc[5]	Level of flex[7]	Level of Comp[1]	Level of chan[4]	Level of Indep[2]
Chemical engineering	Level of flex[7]	Level of inter[3]	Level of Indep[2]	Level of Comp[1]	Level of chan[4]	Level of systems[6]	Level of unc[5]
Civil engineering	Level of Comp[1]	Level of inter[3]	Level of systems[6]	Level of flex[7]	Level of Indep[2]	Level of chan[4]	Level of unc[5]
Computer science engineering	Level of flex[7]	Level of systems[6]	Level of Comp[1]	Level of Indep[2]	Level of unc[5]	Level of inter[3]	Level of chan[4]
Electrical engineering	Level of flex[7]	Level of Indep[2]	Level of systems[6]	Level of Comp[1]	Level of inter[3]	Level of unc[5]	Level of chan[4]
Industrial and systems engineering	Level of flex[7]	Level of systems[6]	Level of inter[3]	Level of Comp[1]	Level of chan[4]	Level of Indep[2]	Level of unc[5]

Table 4.17 (Continued)

Majors of study	1	2	3	4	5	6	7
Master business administration	Level of systems[6]	Level of Comp[1]	Level of inter[4]	Level of flex[7]	Level of Indep[2]	Level of chan[3]	Level of unc[5]
Mechanical engineering	Level of flex[7]	Level of inter[3]	Level of systems[6]	Level of Comp[1]	Level of Indep[2]	Level of chan[4]	Level of unc[5]
Petroleum engineering	Level of Comp[1]	Level of Indep[2]	Level of inter[3]	Level of systems[6]	Level of flex[7]	Level of unc[5]	Level of chan[4]
Software engineering	Level of inter[3]	Level of systems[6]	Level of unc[5]	Level of flex[7]	Level of Indep[2]	Level of chan[4]	Level of Comp[1]
Other	Level of comp[1]	Level of Indep[2]	Level of systems[6]	Level of chan[4]	Level of unc[5]	Level of inter[3]	Level of flex[7]

*Comp[1] Complexity, *Indep[2] Independence, *inter[3] Interaction, *chan[4] Change, *unc[5] Uncertainty, *systems[6] Systems worldview, *flex[7] Flexibility.

The Fuzzy AHP analysis provides the overall students' preference for the ST approaches. The aggregate weight reveals that the following majors all prefer holistic thinking rather than reductionist thinking, namely aerospace engineering major, biomedical engineering major, industrial and systems engineering major, master business administration major, and software engineering students major. On the other hand, the other majors i.e., chemical engineering, civil engineering, computer science, electrical mechanical, and petroleum, tend to favor the reductionist approach of ST rather than the holistic thinking. Figure 4.18 and Table 4.18 provides the overall score of the students' ST approach preference.

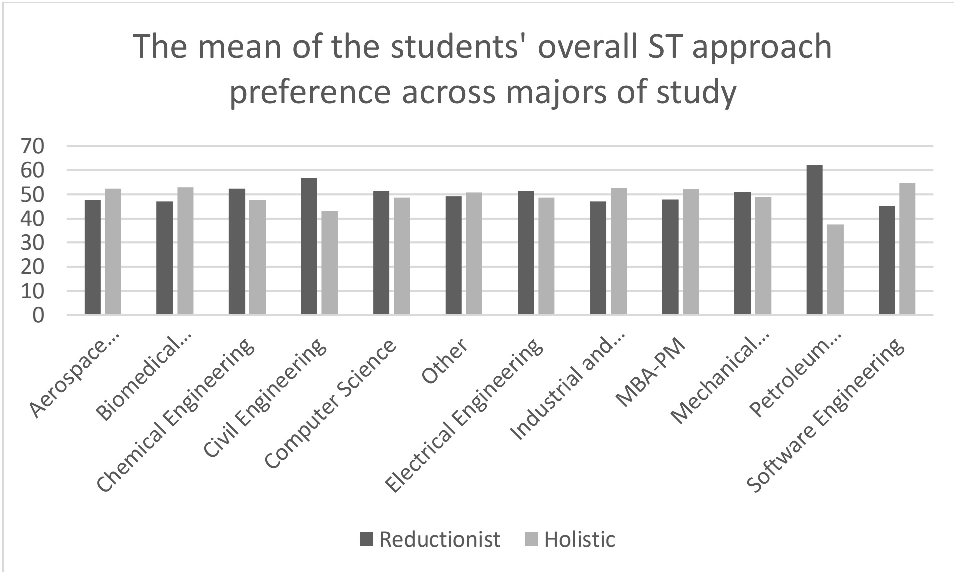

Figure 4.18 Cluster column chart for different majors of study's mean ST approach preference

Table 4.18 The ranking of the most preferred ST approach for different majors of study

Majors of study	**1**	**2**
Aerospace engineering	Holistic approach	Reductionist approach
Biomedical engineering	Holistic approach	Reductionist approach
Chemical engineering	Reductionist approach	Holistic approach
Civil engineering	Reductionist approach	Holistic approach
Computer science engineering	Reductionist approach	Holistic approach
Electrical engineering	Reductionist approach	Holistic approach
Industrial and systems engineering	Holistic approach	Reductionist approach
Master business administration	Holistic approach	Reductionist approach
Mechanical engineering	Reductionist approach	Holistic approach
Petroleum engineering	Reductionist approach	Holistic approach
Software engineering	Holistic approach	Reductionist approach
Other	Holistic approach	Reductionist approach

4.2.7 Aggregate results of the preference of the bachelors' students based on their current year of study

This subsection delves into the preference of bachelor's students specifically to illustrate their preferences based on the year of study. It is important to note that the goal of this section is to gain a better understanding of the student's perceptions, rather than to generalize, as the number of students in each category is different. Figure 4.19 presents a cluster column chart that shows the mean preference of students from different years of study i.e., Freshman students, Sophomore students, Junior students, and senior students.

The results of the Fuzzy AHP analysis reveal the aggregate priority weights for the freshman students to show that their most favored dimensions are the level of flexibility 21.18%, interaction 14.53%, and systems worldview 14.38%; followed by the level of change 14.15%, uncertainty 12.38%, independence 12.08%, and complexity 11.27%. Similarly, for sophomore students, their most preferred dimensions are the level of flexibility 16.99%, complexity 14.61%, and interaction 14.49%; followed by the level of systems worldview 14.40%, independence 14.15%, uncertainty 12.75%, and change 12.57%. As for junior students, the most favored dimensions are the level of flexibility, 15.95%, interaction 15.39%, and complexity 14.98%; followed by the level of systems worldview 14.77%, independence 13.94%, change 12.68%, and uncertainty 14.77%. Lastly, the senior students most favored dimensions are the level of flexibility 17.72%, systems worldview 16.60%, and interaction 15.44%; followed by the level of complexity 13.22%, independence 13.03%, uncertainty 12.48%, and change 11.47%. Table 4.19 summarizes the ranking of the aggregate score of each dimension across the different bachelor years of study.

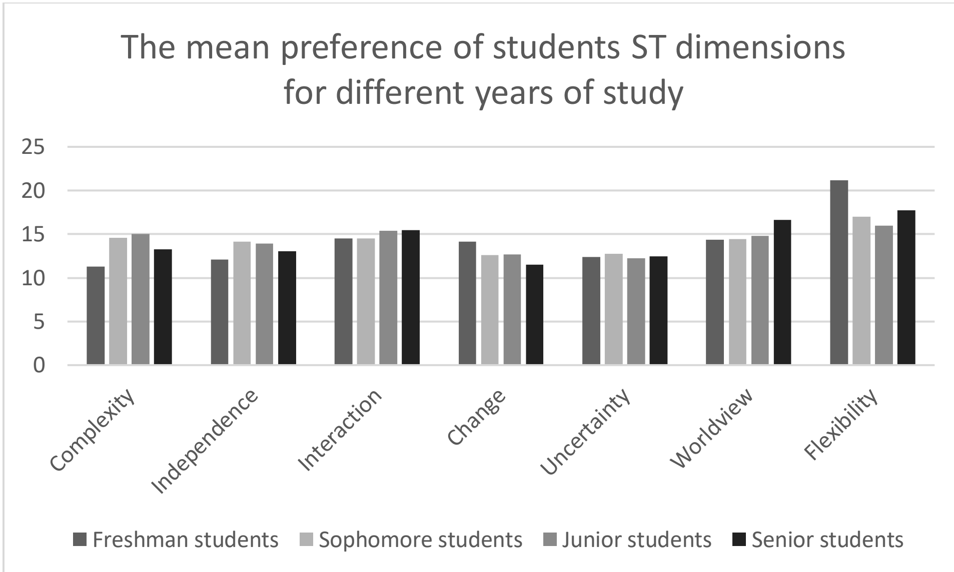

Figure 4.19 Aggregate priority results of bachelor's students based on their current year of study (Freshman students n=41, Sophomore students n=80, Junior students n=110, Senior students n=65)

Table 4.19 The ranking of the seven dimensions for different bachelor's degree year of study

Ranking	Freshman students	Sophomore students	Junior students	Senior students
1	Level of flexibility	Level of flexibility	Level of flexibility	Level of flexibility
2	Level of interaction	Level of complexity	Level of interaction	Level of systems worldview
3	Level of systems worldview	Level of interaction	Level of complexity	Level of interaction
4	Level of change	Level of systems worldview	Level of systems worldview	Level of complexity
5	Level of uncertainty	Level independence	Level of independence	Level of independence
6	Level of independence	Level of uncertainty	Lev of change	Level of uncertainty
7	Level of complexity	Level of change	Level of uncertainty	Level of change

The overall students' most preferred ST approach is also studied for different years of study within the bachelor's students. The results show that freshman students prefer the holistic approach as the mean priority is 54.97%. For the sophomore students and junior students, both groups prefer the reductionist approach to ST, since their respective mean weights are above 52%. Finally, senior students prefer the holistic approach because the weight is above 50%. Figure 4.20 and Table 4.20 illustrate the mean of the weights attributed by each group and the overall students' ranking of the approaches.

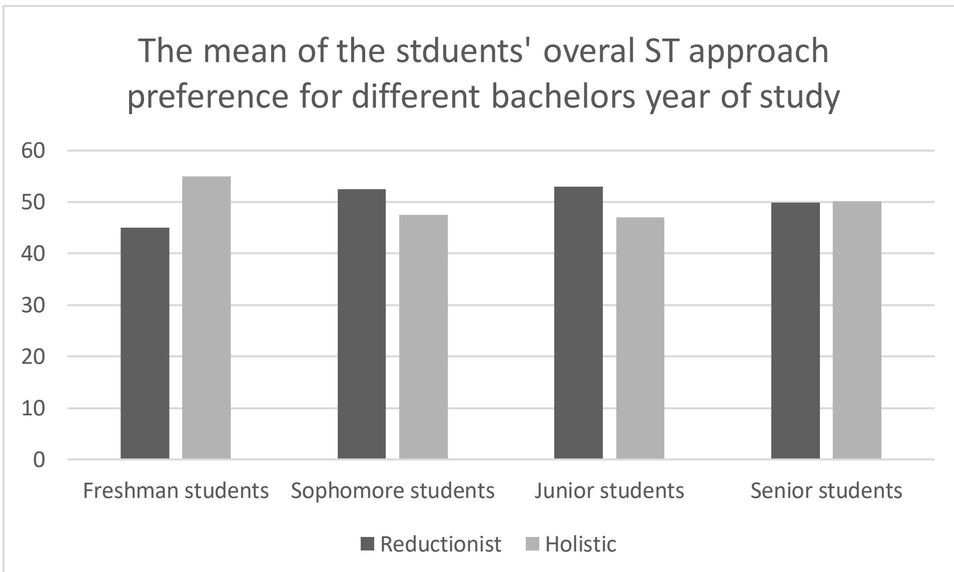

Figure 4.20 Cluster column chart for different years of study for bachelors' students

Table 4.20 The ranking of the students most preferred ST approach for different years of study of bachelor's degree

Ranking	**Freshman students**	**Sophomore students**	**Junior students**	**Senior students**
1	Holistic approach	Reductionist approach	Reductionist approach	Holistic approach
2	Reductionist approach	Holistic approach	Holistic approach	Reductionist approach

4.3 Statistical evaluation and analysis of results

Analyzing the results obtained from the fuzzy AHP analysis of the different grouped students reveals differences between these groups depending on the clustering factors. To statistically justify and verify the significant differences, the use of statistical testing is necessary. Hence, this section aims to statistically study the effect of each factor on the overall students' preferences of both the seven dimensions, and the ST approaches. ANOVA and Welch's t-test are used to evaluate the significance. Welch t-test is an independent-sample t-test used to compare the mean between the groups since the sample size of each sub-group is not constant. Furthermore, Welch independent sample test is a more general test as it does not require the assumption of equal variance between the samples to compare. The ANOVA test evaluates the significant difference between more than two groups. SPSS software is used to study the significance of each factor in each group. To perform the analysis, the data was re-coded. For instance, to study the effect of gender differences, the data was recoded such that gender female was given a value of 1 while the male was given a value of 2.

4.3.1 Statistical evaluation of gender difference

We perform a statistical testing using independent sample t test in order to check the significance of the different results obtained from the analysis of the Fuzzy AHP. Table 4.21 provides the significance, hypothesis, and result of both tests. The results show a significant difference between the two genders in the level of complexity (H1), independence(H2), and flexibility (H7). Thus, female students have a different preference than male students regarding these dimensions, and the previously described differences are statistically supported.

Table 4.21 Significance results associated with independent sample t-test regarding seven dimensions of ST and overall ST approach for gender difference

Comparison between 2 groups of genders	Independent sample Welch test	Hypothesis
Level of complexity	<.001***	**H1**
Level of independence	.008**	**H2**
Level of interaction	.887	H3
Level of change	.610	H4
Level of uncertainty	.288	H5
Level of systems worldview	.211	H6
Level of flexibility	.008**	**H7**
Holistic approach	.098*	H8
Reductionist approach	.098*	H9

<0.10 *, <0.05**, <0.001***

4.3.2 Statistical evaluation of learning modality difference

In order to statistically assess differences between the groups of students based on their learning modality, the dataset was recoded and statistically tested using SPSS software. Table 4.22 provides the significance results of the statistical tests for independent sample test. According to the results in Table 4.22, there is a statistical difference between distance and on-campus students in their preferences for the level of flexibility (H7). Therefore, the learning modality (distance or on-campus) does affect the preference of the students towards the flexibility level.

Table 4.22 Significance results associated with independent sample t-test regarding seven dimensions of ST and overall ST approach for learning modality difference

Comparison between 2 groups of learning modality	Independent sample Welch test	Hypothesis
Level of complexity	.115	H1
Level of independence	.591	H2
Level of interaction	.567	H3
Level of change	.064*	H4
Level of uncertainty	.494	H5
Level of systems worldview	.311	H6

Table 4.22 (Continued)

Comparison between 2 groups of learning modality	**Independent sample Welch test**	**Hypothesis**
Level of flexibility	.050**	**H7**
Holistic approach	.890	H8
Reductionist approach	.890	H9

<0.10 *, <0.05**, <0.001***

4.3.3 Statistical evaluation of GPA difference

In order to statistically evaluate the differences between groups of students based on their GPA scores, the dataset was recoded and statistically tested using SPSS software. Each GPA interval is provided a specific number, then tested on the seven dimensions and overall ST approaches. Table 4.23 provides the significance results for the statistical testing of ANOVA. According to the results in the Table 4.23, students with different GPA scores significantly differ in their preferences for the level of systems worldview (H6). Therefore, the GPA score does affect the students' preference towards the systems worldview level.

Table 4.23 Significance results associated with ANOVA regarding seven dimensions of ST and overall ST approach for different GPA score

Comparison between different GPA interval scores	**ANOVA**	**Hypothesis**
Level of complexity	.086*	H1
Level of independence	.079*	H2
Level of interaction	.957	H3
Level of change	.889	H4
Level of uncertainty	.463	H5
Level of systems worldview	**.043****	**H6**
Level of flexibility	.450	H7
Holistic approach	.060*	H8
Reductionist approach	.060*	H9

4.3.4 Statistical evaluation of differences based on program of study

In order to statistically evaluate the describes differences between the students from different programs, the dataset was recoded and statistically tested using SPSS software. Each program of study (bachelors, masters, or doctoral program) was provided a specific number and then tested for the seven dimensions and overall ST approaches. Table 4.24 provide the significance results of the statistical testing of ANOVA. According to the results in the Table 4.23, there exists statistical significance in the preferences of students from different programs of study with respect to the level of independence (H2), and uncertainty (H5), and flexibility (H7).

Table 4.24 Significance results associated with ANOVA regarding seven dimensions of ST and overall ST approach based on program of study

Comparison between the programs of study	ANOVA	Hypothesis
Level of complexity	**.039****	**H1**
Level of independence	.507	H2
Level of interaction	.662	H3
Level of change	.178	H4
Level of uncertainty	**.044****	**H5**
Level of systems worldview	.441	H6
Level of flexibility	**.050****	**H7**
Holistic approach	.388	H8
Reductionist approach	.388	H9

<0.10 *, <0.05**, <0.001***

4.3.5 Statistical evaluation of differences based on the major of study

In order to statistically evaluate the described differences between the students' preferences based on their major of study, the dataset was recoded and statistically tested. Each major of the study was provided a specific number and then tested for the seven dimensions and overall ST approaches. Table 4.25 summarizes the significance of the statistical tests that evaluate the differences between the majors of study. According to the results, in Table 4.25, a significant difference exists between the preference of the students from different majors to the level of complexity (H1).

Table 4.25 Significance results associated with ANOVA regarding seven dimensions of ST and overall ST approach based on the major of study

Comparison between different majors of study	ANOVA	Hypothesis
Level of complexity	**.036****	**H1**
Level of independence	.991	H2
Level of interaction	.127	H3
Level of change	.939	H4
Level of uncertainty	.710	H5
Level of systems worldview	.933	H6
Level of flexibility	.343	H7
Holistic approach	.372	H8
Reductionist approach	.372	H9

<0.10 *, <0.05**, <0.001***

4.3.6 Statistical evaluation of differences between different years for undergraduate students

In order to statistically evaluate the described differences between the students' preferences based on their major of study, the dataset was recoded and statistically tested using SPSS software. Each major of study was provided a specific number and then tested for the seven dimensions and overall ST approaches. Table 4.26 suggests no significant difference exists between the student's preference with respect to the seven dimensions and the overall ST approach.

Table 4.26 Significance results associated with ANOVA and independent sample t-test regarding seven dimensions of ST and overall ST based on bachelors' students' year of study

Comparison between different undergraduate year of study	ANOVA	Independent sample Welch test	Hypothesis
Level of complexity	.176	.072	H1

Table 4.26 (continued)

Comparison between different undergraduate year of study	**ANOVA**	**Independent sample Welch test**	**Hypothesis**
Level of independence	.500	.359	H2
Level of interaction	.780	.771	H3
Level of change	.273	.325	H4
Level of uncertainty	.980	.980	H5
Level of systems worldview	.587	.629	H6
Level of flexibility	.079*	.141	H7
Holistic approach	.071*	.083	H8
Reductionist approach	.071*	.083	H9

<0.10 *, <0.05**, <0.001***

4.4 Predicting the preference of the students using machine learning

Forecasting and predicting the students' preferences permit effective support and guidance to improve the student's learning experience. Using machine learning to predict the priority and importance of the students towards ST will help instructors and administration have a prior understanding of the student's profile by only investigating the demographic and priority attributed to each level of ST.

The analysis entailed four main steps: data collection, data preparation, model construction, and model evaluation, as described in Figure 4.21.

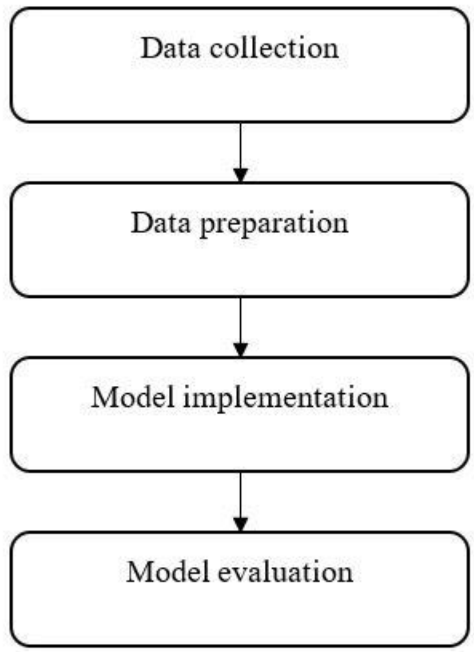

Figure 4.21 Flowchart describing the steps for machine learning analysis

- Data collection: the analysis is based on the students' preferences from Mississippi State University. Therefore, we retrieved the analysis results from Fuzzy AHP as they report the priority weights attributed to the seven dimensions and overall ST approach. The dataset contains 372 observations.
- Data preparation: five incomplete data were observed in the dataset. The missing values were replaced using an imputation procedure using SPSS software. In addition to missing data handling, the categorical factors of the dataset were encoded using the one-hot encoder. The data categorical variables included gender, learning modality, program degree of study, and GPA score. Additionally, a new attribute was defined named "Holistic Viewer". This new attribute is defined such that the values above the threshold 50 from the holistic priority

outcome are set to 1 otherwise a value of 0 is attributed. Therefore, the Holistic Viewer variable is a binary variable that will be used as the target variable.

- Model implementation: this step includes constructing the different machine learning models to predict the Holistic viewers using the prepared features/factors. The models include (Logistic regression, Support Vector Machine SVM, Naïve Bayes, decision tree, and ensemble learning models).
- Model evaluation: this step checks the key measurement parameters previously described in the methodology section. The measurement parameters of each model will be used to compare the models to determine the best model.

4.4.1 Model construction

Among the 372 observations, a data splitting is performed such that a training and testing split is defined. The training set contains 297 (80%) observations, while the testing set contains 75 (20%) observations. All the models are fitted using the training and testing set, and the predictions are based on the previously described variables. The machine learning algorithms used include logistic regression (LR), Support vector machine (SVM) with two kernels (i.e., RBF and linear), Naïve Bayes (NB), decision tree (DT), voting classifier (VC), Bagging, and random forest (RF).

4.4.2 Model evaluation

The results of the models are evaluated for each model using the measurement parameters (accuracy, precision, recall, and F1). The results obtained are reported per algorithm in the following Table 4.27.

Table 4.27 Performance measures of the models

Machine learning model		Accuracy	Precision	Recall	F1
Logistic regression (LR)		0.72	0.71	0.73	0.72
Support Vector Machine (SVM)	Linear kernel	0.71	0.71	0.67	0.69
	RBF kernel	0.66	0.70	0.57	0.63
Naïve Bayes (NB)		0.72	0.7	0.76	0.73
Decision Tree (DT)		0.61	0.61	0.59	0.60
Random Forest (RF)		0.77	0.73	0.80	0.78

Table 4.27 summarizes the performances of the used machine learning models. The evaluation measures used to determine the performance are accuracy, precision, recall, and F1. In addition to the illustrated models, other ensemble learning methods are used to investigate the possibility to increase the accuracy of the predictions. A voting classifier is used that includes three diverse classifiers namely LR, Random Forest classifier, and SVM. The result of the accuracy estimates that the LR provides an accuracy of 70.67%, RF provides an accuracy of 68%, and SVC 66.67%. The voting classifier achieves a 71% accuracy. Additionally, bagging ensemble learning is used. Overall, the accuracy achieved by the bagging classifier is 76% accuracy.

Therefore, we conclude that the best-performing model is the random forest as it outperformed all the machine learning models. The accuracy achieved in predicting the holistic thinker students is 77.33% (see Figure 4.22). Additionally, the results reveal that the suggested model can be used to substitute the survey question of AHP/Fuzzy AHP which contains 28 questions in addition to the demographic questions. Therefore, the machine learning model can predict the student's ST preference only based on the general demographic factors and own preference of the seven dimensions.

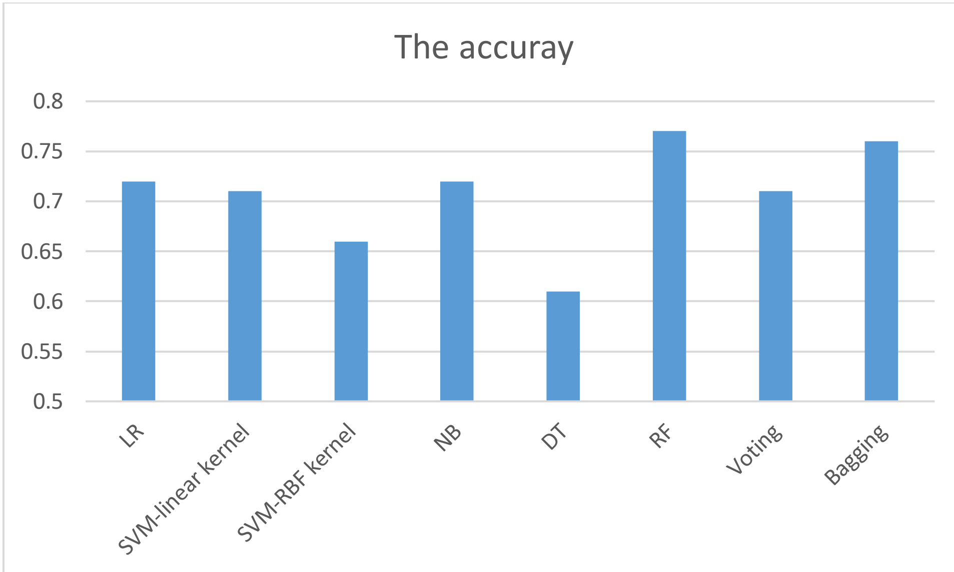

Figure 4.22 Accuracy prediction results using different machine learning models

4.5 Summary response to the research questions and interpretation

This section of the dissertation aims to summarize the answers of the developed research question obtained through the analysis results.

4.5.1 Response to the first research question

4.5.1.1 Response to the research question about overall students' performance

Through the performed analysis of AHP and Fuzzy AHP, we were able to identify the dimensions that students favored the most and the least. Flexibility, systems worldview, and interaction were the top three preferred dimensions, while uncertainty is the least favored. The overall aggregate result of the student's preference showed that the most preferred approach of ST is reductionist over holistic. Figure 4.5 offers a more detailed breakdown of the priority ranking of student's preferences.

4.5.1.2 Response to the research question about students' preferences based on general factors

This subsection of the dissertation, the goal is to provide a summary of the responses to the research questions introduced in Chapter I. Section 4.4 of the dissertation addresses the sub-research questions related to the primary question, which deals with the most important dimension of ST. The first sub-research question "What is/are the most important dimension(s) of systems thinking?" is composed of six questions, each targeting a specific factor. The second sub-research question "what is the overall preference of students? Is it holistic thinking of reductionist thinking?" also contains six questions. The answers to both first questions from both sub-research questions are provided simultaneously, as they indicate the preference based on each specific factor. The goal was to have a general perception of each group's favored approach and not to compare as the answer of this later is summarized on the next section.

The answer for questions 1. a.i and 1. b.i are answered in section 4.4.2 that are related to the gender factor. The result shows that female students' most favored dimension is the level of flexibility followed by the level of systems worldview, and the least favored dimension is the level of independence. In contrast, male students' most favored dimension is the level of flexibility followed by the level of complexity, and the least favors is the level of uncertainty. Additionally, female students prefer the holistic approach of systems thinking, while male students prefer the reductionist approach. The answer for questions 1.a.ii and 1.b.ii are answered in section 4.4.3 that are related to the learning modality factor. The result shows that on-campus students' most favored dimension is the level of flexibility followed by interaction and their least favored dimension is the level of uncertainty, while distance students' most favored dimension is the level of complexity followed by the level of systems worldview and their least favored dimension is the level of change. Also, distance and on-campus students both prefer the reductionist approach of ST. The answer to questions 1.a.iii and 1.b.iii are answered in section 4.4.4. The result shows that the most favored dimension for both students with a GPA of 4.0 and a GPA of 3.50-3.99 score is the level of flexibility followed by the level of systems worldview. For the students with a GPA of 3.00-3.99 score, the most favored dimension is the level of complexity followed by the level of flexibility, for the students with a GPA of 2.50-3.99 score is the level of flexibility followed by the level of interaction, and lastly, for the students with GPA of 2.00-2.49 & 1.50-1.99 is the level of independence and the level of uncertainty. Additionally, students with a GPA of 4.0 and GPA of 3.50-3.99 both prefer the holistic approach of ST while all other students with GPAs of 3.00-3.49, 2.50-2.99, 2.00-2.49&1.50-1.99 prefer the reductionist approach of ST. These results are consistent with the literature that suggests that the level of ST is highly related to the school performance of the students (Hopper and Stave, 2008). Hence, the students with higher performance and GPA the more they understand the importance of ST holistic thinking but also the higher is their level of ST as suggested by the literature. The answer to questions 1.a.iv and 1.b.iv are answered in section 4.4.5. The result shows that the most favored dimension of bachelor's students is the level of flexibility followed by the level of interaction, for the master's students most favored dimension is the level of complexity followed by the level of systems worldview, while for the Ph.D. students is the level of complexity followed by the level of independence. Additionally, the result report that bachelor students prefer the reductionist approach while both masters and Ph.D. students prefer the holistic approach of ST. The findings are consistent with the results in the literature. The results of the overall ST preference approach align with the results from assessment of student's educational level of Hossain et al. (2020) who determines that bachelor's degree students are low-holistic thinkers compared to graduate's degree students who are holistic thinkers. Concerning the answer to questions 1.a.v and 1.b.v, they are answered in section 4.4.6. The students from civil engineering and petroleum engineering majors prefer the level of complexity, students from software engineering majors prefer the level of interaction, students from biomedical engineering and MBA majors prefer the level of systems worldview. Meanwhile, students from other majors including aerospace engineering, chemical engineering, computer science engineering, electrical engineering, industrial and systems engineering, and mechanical engineering prefer the level of flexibility. Additionally, students from majors such of aerospace engineering, biomedical engineering, industrial and systems engineering, MBA, and Software engineering prefer the holistic approach of ST. on the other hand, students from majors of chemical engineering, civil engineering, computer science engineering, electrical engineering, mechanical engineering, and petroleum engineering prefer the reductionist approach of ST. Lastly, the answer of questions 1.a.vi and 1.b.vi are answered in section 4.4.7 of the dissertation. All bachelor students' most preferred level of ST is the level of flexibility. Also, freshman students and junior students prefer the reductionist approach of ST; while sophomore and senior students prefer the holistic approach of ST.

4.5.1.3 Response to the research question about the significance of general factors' effect

Based on the analysis of the Fuzzy AHP results and the performed statistical testing, we observed that students' preferences variation towards the seven dimensions of ST are statistically different and does depend on various factors. These preferences are influenced by several factors, such as gender, learning modality, academic performance (GPA), program of study, and major of study. The gender of the student (female or male) affects the importance attributed to the complexity, independence, and flexibility level of systems thinking. For instance, male students tend to prioritize complexity and independence levels more than female students. This provides information of how gender can affect the priority attributed and the cognitive thinking of both genders. The learning modality is also one factor that affects the priority ranking attributed to the flexibility level of the students. Finally, the student's academic performance, the GPA, affects the priority score or ranking of the level of systems worldview. These results show that the students with higher GPA prefer to analyze the system by looking at it as a "Big picture" instead of the little details and avoid the traditional "cause-effect" analysis (Nagahi, 2021). This results further justifies the preference of the students with higher GPA to the holistic approach of ST. As illustrated in Figure 4.14, students with a GPA score of 4 prefer the systems worldview level more than the other students with different GPA scores. Furthermore, students with higher GPA scores tend to provide higher importance to the level of systems worldview. The program of study affects the preference of students. The students enrolled in bachelor's, master's, or doctoral programs significantly differ in the attributed importance towards the level of complexity, uncertainty, and flexibility. The results show that PhD and master's degree students prefer the level of complexity more than the bachelor's degree students as depicted on Table 4.15, while bachelor's degree students prefer the level of uncertainty and flexibility more than the other levels. The obtained for complexity results are similar to the results obtained while assessing the level of ST of the students based on the educational level of the students in the study of Hossain et al. (2020). Also, bachelor's degree students prefer the level of uncertainty and flexibility more compared to other students. Another factor contributing to the precision of the students' preference towards the complexity level is the major of the study. For illustration, petroleum engineering and civil engineering students attribute the highest ranking and priority weights to the level of systems worldview. Additionally, MBA project management students rate the level of systems worldview as the second most important factor. Computer science students reveal that the level of systems worldview is the third most important dimension. On the other hand, chemical engineering, electrical, industrial and systems, and mechanical engineering students all provide the fourth priority to this dimension compared to the students from other majors of study. In the contrast, software engineering students provide the lowest ranking to this level and so is their least favored dimension. This determines that the major of study can affect the priority attributed by the students to the seven dimensions and that different majors of study may shape the students' perceptions differently based on the environment. Lastly, the statistical test reveals that undergraduate students do not have any significant difference in their provided priority ranking. Although the findings in section 4.4.7 cannot be generalized, the results can be utilized as a guide to have a prior comprehension of the student's preferences. For instance, freshman students rate the complexity as the least important, which should bring attention to educators to investigate and understand their choices.

4.5.2 Response to the second research question

The second research question explores the feasibility of using machine learning techniques to predict the preferred approach of students towards ST. After implementing the various machine learning algorithms, we arrived at the conclusion that anticipating students' favored ST approach is achievable. The accuracy of the prediction using the Random Forest classifier algorithm stands at 77.33%. In other words, the Random Forest classifier model help in constructing the ST preference profile of the student. Using the seven dimensions priority, the demographic and general factors of a new student, Radom Forest classifier permit to build the student's profile. This can help institutions have a prior understanding of student's perception about ST, their manner to approach complex systems, and anticipate students who may find difficulties at school.

CHAPTER V

CONCLUSION

This chapter aims to provide an overview of the dissertation, including a summary of each chapter's findings and outcome, the study's limitations, and recommendations for future studies.

5.1 Summary of the funding

The continuous change, development, and introduction of new technologies to the systems continue to increase in the interrelation between the elements and the complexity of the systems. The complexity increase requires the skilled workforce to deal with and solve complex systems problems. “Systems thinking” has captured the attention of professional and scholars as it has been identified as a potential approach that helps individuals effectively and efficiently solve complex systems. This dissertation focuses on studying the students’ preferences for the ST approaches rather than their assessment since they are the future and consist future workforce. The dissertation started with Chapter I which introduces the motivation and problem statement. It also discusses the study's significance to highlight the literature's contribution. Then, the chapter provides the dissertation's main hypothesis and research questions. Finally, the dissertation follows a theoretical framework structure to organize the work.

Chapter II provides an extensive literature review on ST and its importance. This chapter begins by defining the concept of ST and providing its background. While focusing on the field of education, this chapter also highlights other applications and sectors that use systems thinking.

Furthermore, chapter II aims to investigate the previous research papers about students' ST capabilities and the impacting factors; but also summarizes the different developed assessment instruments of ST. Finally, the chapter ends by revealing the proposed theoretical model. The proposed theoretical model of the dissertation consists of studying the preference of the student for both the holistic versus reductionist approach and the relative importance of the seven dimensions of the ST instrument. The used instrument is a validated tool developed by Jaradat (2015).

Chapter III presents the analysis methods used in the dissertation. First, the chapter introduces data collection, including survey design, the procedure followed to collect the data, the material used, and the data description (frequencies of students' demographics). Second, the chapter reveals the data analysis techniques, namely the Analytic Hierarchy Process (AHP) and its application. Next, the multi-criteria decision analysis technique Fuzzy Analytic Hierarchy Process (Fuzzy AHP), and its implementation are discussed in the chapter since the study relies on the use of a supporting tool to validate the obtained results. Lastly, this chapter introduces the machine learning techniques used for predicting the students' preference for ST holistic approach.

Chapter IV provides the results obtained from analyzing the collected data using both AHP and Fuzzy AHP analysis. The results show that overall students prefer the reductionist approach over the holistic approach of ST since the mean priority weight provided by the students is 50.41% for the holistic compared to 49.58% for the reductionist. The decision was tough, as reflected by the overall importance score. Similar to assessing the student's level of ST skills, there is no good or bad preference as in some circumstances reductionist thinking can be more appropriate and suitable. Also, the analysis provides valuable information concerning the students' preferences regarding the seven dimensions of ST. Students tend to prefer the flexibility level over the other six dimensions. The level of flexibility is the dimension that describes the preference for alternative plans while dealing with a complex system. In other words, the students find that accommodating the continuous change and modification in the complex systems approach is more important. According to the students, being open and adapting to new situations and plans to find the optimum solution is vital. Additionally, students value the importance of having the ability to solve problems in unstable circumstances. On the other hand, the result shows that the students think the least important dimension is the level of uncertainty, which describes the willingness and preference to make decisions even with incomplete information about the system. This reveals that the students do not prefer the level that requires dealing with complex systems in an unpredictable and ambiguous environment. Therefore, our findings suggest that more attention should be paid to improving students' preference for the level of uncertainty. For instance, this can be achieved by asking the students to study a real-life complex system and providing little information about it. Then, under supervision, the students will explore the system and prepare the possible solution with the available knowledge and determine the optimum solution. This can help the students feel more comfortable and understand the importance of dealing with uncertainty while mitigating complex systems.

Furthermore, this dissertation studied the effect of general factors (such as demographic factors) on the preference of the students to reveal that gender, learning modality, GPA score, the program of study, and major of study all contribute to some of the levels of ST. The gender of the student affects the priority and preference of the student toward the level of complexity and flexibility. For illustration, male students prefer and rate the level of complexity to be more important compared to their counterparts (female students). This suggests that female students require more support in the level of complexity because this level is their second least favored dimension. This can help female students increase their willingness to work with multidimensional problems and recognize the traits of complex system problems. The learning modality (distance or on-campus) affects the priority and importance associated with the students' preference to flexibility level. Also, the student's preference to the complexity, uncertainty, and flexibility level change depending on the program of study (Bachelor, Master, Doctorate). Among the impacting factors that affect the importance attributed to the level of systems worldview is the GPA score of the student. Lastly, the major of study is an impacting factor that affects the priority provided by the student to the level of complexity.

This presented research provides insights about the students' preference towards the approaches of ST i.e., systemic versus less systemic, or in other words holistic versus reductionist. For example, the survey results show that female students prefer the holistic view and male students prefer the reductionist view. Still, the statistical analysis reveals that no significant difference is found. The results are coherent with the assessment results found in the literature (Stirgus, 2019; Sirgus, 2019, Nagahi et al., 2020). Additionally, the aggregate results show that students with high GPA scores tend to prefer the holistic approach more. Although the results of the students' priority attribution towards the approaches were not significant, the result of the overall aggregate mean aligns with the student's assessment (Nagahi et al., 2020). Also, the aggregate results show that master's and doctoral students prefer holistic thinking while bachelor students prefer reductionist thinking. These results can be due to the experience and comfort of the students in dealing with complex systems, which tend to enhance the student's personal preferences. Hossain et al. (2020) suggested that the individual's level of education may improve their level of ST within a limit.

To conclude, the identification of the student's preference for the ST approaches in addition to the ranking provided to the seven dimensions, and the factors that impact these preferences provide direct insights to focus on the necessary capabilities to improve the student's comfort and abilities towards these dimensions.

The goal of the dissertation was to use the results obtained from the study of the students' preferences (the seven dimensions priority scores) and construct a machine learning model capable of predicting the student's holistic thinking preferences. In addition, this objective permit building a model that can replace the traditional AHP questionnaire used to determine the ST holistic/reductionist approach preferences. This is especially important since the overall number of questions can be reduced from 28 (pairwise comparisons) to 7 in addition to the general questions. The 7 questions will be to assign a priority score for each of the seven dimensions. The dissertation presents a machine learning model "Random Forest" capable of predicting the student's preference of ST holistic approach by 77%

The presented dissertation is based on a recent real-life dataset that was used to determine the preference of the students to ST using machine learning techniques. This dissertation is one of the unique studies that implemented machine learning to SE through the use of ST. To conclude, a list of the study's outcome are summarized as follow:

- The study of the students' priorities permits to obtain valuable information concerning their preferences by identifying the most and least preferred dimensions. These results can be used to train and provide the necessary aid and support to let the student feel more confident and comfortable even when dealing with their least favored dimensions.

- The results allow to determine that the education sector needs to introduce more real-life examples for the students to experience complex systems problem solving and understand the importance of all the levels. This can be achieved through training and adding new classes that support holistic thinking.
- The machine learning model can predict newly recruited students who prefer holistic/reductionist thinking and intervene early to provide the necessary tutoring.

5.2 Limitations and future recommendations

Despite the positive research findings, there exists certain limitations within the study. The AHP analysis is a simple and extremely powerful decision-making tool that has been widely used. However, the survey questionnaire of AHP requires quite a large number of pairwise comparisons for the decision maker to judge. This is a drawback as some of the students did not complete the survey, which led to losing some participants to keep only the students who completed the survey. Although the study includes students from different departments, most students were only from engineering or business (MBA) departments, and some of the engineering majors contained few students. Additionally, the current study tried to include students from different levels of education, and only a small number of Ph.D. students participated in the study. Therefore, future experiments should include more students from other departments such as (military engineering, educational engineering, architecture, etc.), and more PhD students. To have a better comparison between the groups, future work is recommended to use equal sample sizing. The dissertation study focuses mainly on reductionist and holistic approaches. Hence, the prediction was based on holistic thinker and included two clusters i.e., the reductionist and the holistic thinker. Therefore, future work can include a third cluster that contains students with a preference to both approaches rather than one.

This presented dissertation forms a foundation for future work and can be extended in different manners. This current study will be extended such as to make use of our current data set to include professionals from different majors in order to check if the students' preferences align with the workforce environment. Investigating the difference between the professional and the actual students will determine which dimensions or approach are more likely to be enhanced for the students to fill in best the job profile. Additionally, this work can be further elaborated by using and implementing more advanced machine learning models such as deep learning techniques in order to increase the predictability accuracy. Also, future studies can perform longitudinal studies to compare and track the change in the students' preferences toward systems thinking. Performing a longitudinal study will permit to determine if there is a change in the preference to the seven dimensions or improvement on the overall ST of the students especially for bachelor's degree students. Although this dissertation includes different factors, introducing the effect of another factor may increase the accuracy of holistic thinkers' predictions. Hence, future works can focus on experience factors such as work experience (internships, co-ops, etc.), high school experience (private or public school), parents' education level, extra curriculum activities, etc.

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APPENDIX A

SURVEY QUESTIONNAIRE

1. How is the level of complexity important to you compared to:

	9	7	5	3	1	3	5	7	9	
The level of complexity: Comfort with multidimensional problems and limited system understanding										**The level of independence:** balance between local-level autonomy versus systems integration
The level of complexity										**The level of interaction:** interconnectedness in coordination and communication among multiple systems
The level of complexity										**The level of change:** comfort with rapidly shifting systems and situations
The level of complexity										**The level of uncertainty:** acceptance of unpredictable situations with limited control
The level of complexity										**The level of systems** worldview: understanding systems behavior at the whole versus part level
The level of complexity										**The level of flexibility:** accommodation of change or modifications in systems or approaches

2. How is the level of independence important to you compare to:

	9	7	5	3	1	3	5	7	9	
The level of independence: balance between local-level autonomy versus systems integration										**The level of interaction**: interconnectedness in coordination and communication among multiple systems
The level of independence										**The level of change**: comfort with rapidly shifting systems and situations
The level of independence										**The level of uncertainty:** acceptance of unpredictable

										situations with limited control
The level of independence										**The level of systems worldview:** understanding systems behavior at the whole versus part level
The level of independence										**The level of flexibility:** accommodation of change or modifications in systems or approaches

3. How is the level of interaction important to you compared to:

	9	7	5	3	1	3	5	7	9	
The level of interaction: interconnectedness in coordination and communication among multiple systems										**The level of change:** comfort with rapidly shifting systems and situations
The level of interaction										**The level of uncertainty:** acceptance of unpredictable situations with limited control
The level of interaction										**The level of systems worldview**: understanding systems behavior at the whole versus part level
The level of interaction										**The level of flexibility:** accommodation of change or modifications in systems or approaches

4. How is the level of change important to you compared to:

	9	7	5	3	1	3	5	7	9	
The level of change: comfort with rapidly shifting systems and situations										**The level of uncertainty:** acceptance of unpredictable situations with limited control
The level of change										**The level of systems worldview:** understanding systems behavior at the whole versus part level

The level of change										**The level of flexibility:** accommodation of change or modifications in systems or approaches

5. How is the level of uncertainty important to you compared to:

	9	7	5	3	1	3	5	7	9	
The level of uncertainty: acceptance of unpredictable situations with limited control										**The level of systems worldview:** understanding systems behavior at the whole versus part level
The level of uncertainty										**The level of flexibility:** accommodation of change or modifications in systems or approaches

6. How is the level of systems worldview important to you compared to:

	9	7	5	3	1	3	5	7	9	
The level of systems worldview: understanding systems behavior at the whole versus part level										**The level of flexibility:** accommodation of change or modifications in systems or approaches

7. In the level of complexity, how is simplicity more important to you compared to complexity

	9	7	5	3	1	3	5	7	9	
Simplicity: avoid uncertainty, work on linear problems, prefer the best solution, prefer small-scale problems										**Complexity:** expected uncertainty, work on multidimensional problems, prefer a working solution, and explore the surrounding environment

8. In the level of independence, how is autonomy more important to you compared to integration

	9	7	5	3	1	3	5	7	9	
Autonomy: preserve local autonomy, a trend more toward an independent decision and local performance level										**Integration:** preserve global integration, a trend more toward dependent decisions and global performance

9. In the level of interaction, how is isolation more important to you compared to the interconnectivity

	9	7	5	3	1	3	5	7	9	
Isolation: inclined to local interaction, follow a detailed plan, prefer to work individually, enjoy working in small systems and interested more in cause-effect solution										**Interconnectivity:** inclined in global interaction, follow a general plan, work within a team, and interested in an identifiable cause-effect relationship

10. In the level of change, how is resistance to change more important to you compared to tolerance to change

	9	7	5	3	1	3	5	7	9	
Resistance to change: prefer taking few perspectives into consideration, focus more on internal forces, like short-range plans, tend to settle things, and work best in stable environment										**Tolerance to change:** prefer taking multiple perspectives into consideration, underspecify requirements, focusing more on external forces, like long-range plans, keeping options open, and working best in a changing environment

11. In the level of uncertainty, how is stability more important to you compared to emergence

	9	7	5	3	1	3	5	7	9	
Stability: prepare detailed plans beforehand, focus on the details, uncomfortable with uncertainty, believe the work environment is under control, and enjoy objectivity and technical problems										**Emergence:** react to situations as they occur, focus on the whole, be comfortable with uncertainty, believe the work environment is difficult to control and enjoy non-technical problems

12. In the level of systems worldview, how is reductionism more important to you compared to holism

	9	7	5	3	1	3	5	7	9	
Reductionism: focus on particulars and prefer analyzing the parts of the system for better performance										**Holism:** focus on the whole, interested more in the big picture, and interested in concepts and abstract meaning of ideas

13. In the level of flexibility, how is rigidity more important to you compared to flexibility

	9	7	5	3	1	3	5	7	9	
Rigidity: prefer not to change, like determined plans, not open to new ideas, and motivated by routine										**Flexibility:** accommodating to change, like a flexible plan, and unmotivated by routine