A SUPPORT VECTOR MACHINE-BASED PROCESS FRAMEWORK FOR PREDICTING STUDENTS' ACADEMIC PERFORMANCE IN OPEN AND DISTANCE LEARNING

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A THESIS SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF THE DEGREE OF DOCTOR OF PHILOSOPHY (PHD) IN ARTIFICIAL INTELLIGENCE AT THE AFRICA CENTRE OF EXCELLENCE ON TECHNOLOGY ENHANCED LEARNING NATIONAL OPEN UNIVERSITY OF NIGERIA

DECLARATION

I, the undersigned **Muyideen Adewale (ACE22140007)**, hereby declare that I am the sole author of this thesis entitled **A Support Vector Machine-Based Process Framework for Predicting Students' Academic Performance in Open and Distance Learning**. To the best of my knowledge, it contains no material previously published or written by another person except where proper acknowledgement has been made. This is a true copy of the thesis, including final revisions. I acknowledge that the copyright of any published works from within the thesis resides with the respective copyright holder(s).

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CERTIFICATION/APPROVAL

This is to certify that this study was carried out by **Muyideen Adewale (ACE22140007)** at the **Africa Centre of Excellence on Technology Enhanced Learning (ACETEL), National Open University of Nigeria, Nigeria**, under my supervision.

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DEDICATION

With profound gratitude, I dedicate this thesis to the Almighty God, whose infinite mercy, grace, and love have brought me to this point. His guidance has been my constant source of strength.

This work is also dedicated to my beloved parents—my father, Mr Adewale Y. Adeleke, whose unwavering support and sacrifices have shaped my journey and to the cherished memory of my late mother, Mrs Adewale N., whose love and sacrifices continue to inspire me.

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LIST OF PUBLICATIONS

This section lists the Scopus-indexed publications that have resulted from the research conducted in this thesis. It includes papers that have been published, accepted, or are currently under review. Each publication is linked to the relevant sections of the thesis, providing a comprehensive overview of how the research contributions have been disseminated.

Title of Paper	**Authors**	**Journal/Conference**	**ISSN**	**Thesis Sections**
Impact of artificial intelligence adoption on students' academic performance in open and distance learning: A systematic literature review, **2024. Under Review.**	MD Adewale, AA Azeta, A Abayomi-Alli, A Sambo-Magaji	Heliyon (Scopus-Indexed Journal. IF= 3.4; CiteScore=4.5).	2405-8440	Chapters 1&2
Artificial Intelligence Influence on Learner Outcomes in Distance Education: A Process-Based Framework and Research Model, **2024. Accepted.**	MD Adewale, AA Azeta, A Abayomi-Alli, A Sambo-Magaji	EAI AFRICATEK 2024 – 7th EAI International Conference on Emerging Technologies for Developing Countries. Held in Nigeria. (Scopus-Indexed Conference Proceedings Published by Springer. CiteScore=0.7)	1867-8211	Chapter 3
A Multilayered Process Framework for Predicting Students' Academic Performance in Open and Distance Learning, **2024. Accepted.**	MD Adewale, AA Azeta, A Abayomi-Alli, A Sambo-Magaji	EAI MTYMEX 2024 – 3rd EAI International Conference on Smart Technologies and Innovation Management. Held in Canada. (Scopus-Indexed Conference Proceedings Published by Springer. CiteScore=1.3)	2522-8609	Chapter 3
An Architectural Framework for Predicting Students' Academic Performance in Open and Distance Learning, **2024. Accepted.**	MD Adewale, AA Azeta, A Abayomi-Alli, A Sambo-Magaji, GE Jokthan, G Onwodi, KM Lawal, and CF	EAI eLEOT 2024 – 10th EAI International Conference on e-Learning e-Education and Online Training. Held in China. (Scopus-Indexed Conference Proceedings	1867-8211	Chapter 3

	Mafiana	Published by Springer. CiteScore=0.7)		

LIST OF PUBLICATIONS (Contd.)

Empirical Investigation of Multilayered Framework for Predicting Academic Performance in Open and Distance Learning, **2024. Published.**	MD Adewale, AA Azeta, A Abayomi-Alli, A Sambo-Magaji	MDPI Electronics (Scopus-Indexed Journal. IF=2.6; CiteScore=5.3)	2079-9292	Chapters 3, 4 & 5
Ethical AI Framework for Integrating Artificial Intelligence in Open and Distance Learning, **2024. Accepted.**	MD Adewale, AA Azeta, A Abayomi-Alli, A Sambo-Magaji, GE Jokthan, G Onwodi, KM Lawal, and CF Mafiana	8th EAI International Conference on Computer Science and Engineering. Held in Laredo, Texas, USA. (Scopus-Indexed Conference Proceedings Published by Springer, CiteScore=0.7)	1867-8211	Chapter 3
The Impact of Artificial Intelligence on Student's Academic Performance in Open and Distance Learning Using Multiple Regression Analysis Technique, **2024. Under Review.**	MD Adewale, AA Azeta, A Abayomi-Alli, A Sambo-Magaji, GE Jokthan, G Onwodi, KM Lawal, and CF Mafiana	Journal of Infrastructure, Policy and Development (Scopus-Indexed Journal. CiteScore=1.0).	2076-3417	Chapters 3, 4 & 5
A Generalised Additive Modelling Approach to Uncovering the Influence of Artificial Intelligence on Student's Success Outcome in Distance Education, **2024. Under Review.**	MD Adewale, AA Azeta, A Abayomi-Alli, A Sambo-Magaji, GE Jokthan, G Onwodi, KM Lawal, and CF Mafiana	AI (Scopus-Indexed Journal. IF=3.1; CiteScore=7.2).	2673-2688	Chapters 3, 4 & 5
Academic Performance Prediction in Distance Education: An Empirical Study Using Enhanced Support Vector Machine	MD Adewale, AA Azeta, A Abayomi-Alli, A Sambo-Magaji, GE Jokthan, G	AI (Scopus-Indexed Journal. IF=3.1; CiteScore=7.2).	2673-2688	Chapters 3, 4 & 5

Model, **2024. Under Review.**	Onwodi, KM Lawal, and CF Mafiana			

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LIST OF ABBREVIATIONS

AAR	AI Alignment and Relevance
AI	Artificial Intelligence
AILA	AI-induced Learning Anxiety
API	Application Programming Interface
ARFC	AI Readiness and Facilitating Conditions
CAAI	Comparative Advantage of AI
CFI	Comparative Fit Index
EEU	Ease and Enjoyment of Use
GPA	Grade Point Average
IC	Interactive Capability

KAUS	Knowledge Absorption and User Satisfaction
MAE	Mean Absolute Error
MSE	Mean Squared Error
ODL	Open Distance Learning
RMSE	Root Mean Squared Error
SEM	Structural Equation Modelling
SQSI	Systems Quality and Social Influence
SVM	Support Vector Machine
TLI	Tucker-Lewis Index
VIF	Variance Inflation Factor

ABSTRACT

The integration of Artificial Intelligence (AI) in education, particularly within Open and Distance Learning (ODL) environments, presents substantial opportunities to enhance academic performance; however, a significant research gap exists in developing a comprehensive framework to predict the impact of AI adoption on student outcomes in ODL systems, especially considering moderating factors like gender and geographical context. This study aims to address this gap by designing, validating, and refining a predictive framework that leverages AI adoption factors to forecast academic performance in ODL settings. A predictive process framework was developed that leverages a mixed-methods approach by integrating Structural Equation Modelling (SEM) and Support Vector Machine (SVM) techniques. Data were collected from 914 students across diverse ODL environments through surveys, capturing variables related to AI adoption such as ease of use, knowledge absorption, and user satisfaction. The

SEM was utilized to validate the relationships between AI adoption factors and academic performance, achieving excellent fit indices (CFI and TLI = 1.000; RMSEA = 0.000). The SVM model was developed to predict academic performance based on the validated factors, with Variance Inflation Factor (VIF) optimization applied to address multicollinearity and enhance model stability. Model performance was evaluated using error metrics including Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). The results demonstrated that AI adoption significantly enhances academic performance when key factors are effectively integrated into ODL systems. The SEM confirmed strong relationships between AI adoption factors and academic performance, while the SVM model achieved high predictive accuracy (MAE = 0.229, MSE = 0.107, RMSE = 0.327). Although the improved SVM model showed a slight increase in error metrics (MAE = 0.295, MSE = 0.180, RMSE = 0.424), it provided more stable and reliable predictions. These findings indicate that the developed framework successfully predicts academic performance and underscores the importance of customizing AI tools to cater to diverse student needs, considering demographic variables such as gender and geographical location. In conclusion, by effectively integrating AI adoption factors into ODL systems, educators and policymakers can significantly enhance academic performance. The developed framework provides a practical tool for predicting and improving student outcomes, thus addressing the initial research gap and contributing to the advancement of AI in education. This implies that targeted AI integration can lead to better educational outcomes, especially when tailored to specific demographic contexts, highlighting the potential for ongoing improvements in AI applications within educational settings.

Keywords: Academic Performance, Artificial Intelligence, AI Adoption factors, Open and Distance Learning, Support Vector Machine.

CHAPTER ONE
INTRODUCTION

1.1 Background to the study

Over the years, the role of Artificial Intelligence (AI) in the educational sector has seen a considerable transformation. This evolution commenced in the 1960s with the advent of programmed instruction and the introduction of computer-assisted learning, establishing the foundational elements of AI within the educational realm. Moving into the 1980s, the field witnessed the rise of intelligent tutoring systems (ITS), which provided customized tutoring experiences by mimicking interactions in one-on-one tutoring situations. The proliferation of the internet during the 1990s and the early 2000s significantly propelled the use of AI in education, enabling the spread of online learning and the adoption of data-driven instructional strategies. The recent decade has been characterized by remarkable progress in machine learning and natural language processing technologies, leading to more advanced AI tools, including adaptive learning platforms and AI-enabled educational assistants. These innovations are pivotal in making education more personalized and widely accessible (Roll & Wylie, 2016).

Artificial intelligence (AI) has garnered significant popularity in educational settings, revolutionizing how people learn and teach. Educators leverage data-driven machine learning (ML) techniques and statistical frameworks to gain valuable insights into student performance patterns (Shen, Chen, Grey, & Su, 2021). AI technology is being utilized to enhance learning outcomes by creating digital labs, teaching platforms, and learning tools that cater for diverse learning needs (Lim, 2020). This approach provides students with personalized instructions, examples, and critiques and fosters the development of critical thinking skills (Wang, Liu, & Tu, 2021).

Contemporary research has started to measure the profound effects of AI on educational achievements. Studies have shown that AI-driven adaptive learning systems significantly enhance student engagement and academic performance. Specifically, adaptive learning systems have increased student participation by approximately 40% and improved test scores by an average of 30% compared to traditional teaching methods (Dabingaya, 2022). This underscores the effectiveness of AI in tailoring education to meet individual learner needs, thereby optimizing learning outcomes. Additionally, using AI in tutoring systems has been proven to reduce learners' study time by about 25% while maintaining or enhancing academic outcomes. This reduction highlights the efficiency of AI in delivering personalized educational experiences, which adapt to the unique learning styles and paces of students, making the educational process more effective (Gligorea, I., Cioca, M., Oancea, R., Gorski, A.-T., Gorski, H., & Tudorache, P., 2023). The application of AI extends beyond enhancing student learning and performance to significantly reducing the workload for educators. Teachers who have implemented AI for administrative tasks have reported an average time saving of 5 hours per week. This additional time has allowed educators to focus more on direct student interaction and instructional improvement, illustrating the comprehensive benefits of AI in educational settings (Gligorea et al., 2023). These findings collectively highlight the transformative potential of AI in education, indicating improved efficiency, personalized learning experiences, and enhanced outcomes for both students and educators.

UNESCO (2019) highlights the role of AI in ensuring equal access to education for all individuals, including those with disabilities, refugees, and those in isolated communities. For instance, telepresence robotics enables students with special needs to attend school remotely, even in emergencies, ensuring inclusivity and accessibility across various locations. AI also revolutionizes collaborative learning by allowing students to choose when and where they study, regardless of their physical location. Asynchronous online discussion groups, a vital component of computer-supported collaborative learning, are monitored using AI systems like machine learning and shallow text processing. AI empowers teachers to gain insights into student discussions, guide their engagement, and enhance their learning experience.

Furthermore, AI facilitates personalized learning by supporting teachers in effectively assisting struggling students. With AI-powered dual-teacher models comprising a teacher and a virtual teaching assistant, routine tasks such as assigning homework and answering common questions can be streamlined. This enables teachers to allocate more time to individual student support and meaningful interactions, ultimately enhancing the quality of education. Many teachers are already embracing AI assistants to collaborate and optimize their teaching practices for the benefit of their students. AI plays a pivotal role in personalized learning and adaptive educational technologies, tailoring learning experiences to meet the diverse needs of students in Open and Distance Learning (ODL). Research has shown that AI-driven personalised learning systems can significantly impact student outcomes and engagement (Makokotlela, 2022). These technologies can adapt to individual learning styles and preferences, enhancing the learning experience.

Artificial Intelligence in Education (AIEd) has emerged as a significant focus in education, driven by advancements in communication and computing technologies (Chen et al., 2020; Hwang et al., 2020). The widespread use of AI tools in education has raised concerns and sparked discussions on improving student learning outcomes (Wang, Liu, & Tu, 2021). While AI in education is a globally recognized topic, its potential is not evenly realized across developed and developing countries.

Inclusion and equity in applying artificial intelligence in education pose significant challenges (Top 5 Challenges of Adopting AI in Education, 2021). Adopting AI in ODL presents challenges related to data privacy, algorithmic bias, and ethical considerations (Reis et al., 2020). Research has emphasized the impact of AI on the political landscape and the need to address data protection and ethical considerations in AI adoption (Reis et al., 2020). Challenges related to data privacy, algorithmic bias, and ethical considerations are critical in AI adoption in ODL. Issues such as data privacy violations and biased algorithmic decision-making can impact student outcomes and educational equity (Pillai & Sivathanu, 2020). Additionally, adopting AI in ODL may raise concerns about the ethical use of student data and the potential for algorithmic discrimination (Lee & Chen, 2022).

Despite the United Nations' efforts to enhance access to high-quality education and foster lifelong learning opportunities (UNESCO, 2022), gender differences persist in the motivation for advanced education involving AI technologies and applications (Squicciarini et al., 2020). However, there is limited evidence regarding the factors contributing to these gender differences, particularly in Africa. Hence, there is a critical need to conduct an in-depth examination of the factors influencing gender disparities in students' motivation to utilize AI technologies and applications within a pan-African framework. Previous systematic reviews have indicated that research on AI in education has primarily focused on developed countries (Roll & Wylie, 2016). As a result, AI in education remains a neglected topic in the developing world, where it is often considered part of an advanced technological discourse that relies on well-established infrastructure and knowledge ecosystems (UNESCO, 2019).

AI systems present new opportunities to promote gender equality and enhance the quality of life, potentially leading to increased productivity and improved job opportunities and services (European Commission, 2018). To foster gender inclusion and equality in adopting AI-based applications in education, researchers must broaden the scope of their studies and explore the factors contributing to gender differences in the utilization of these applications by students in higher education institutions within developing countries. By reducing barriers to learning access, automating administrative processes, and optimizing teaching methodologies to enhance student performance, AI holds great potential to accelerate the realization and development of global education goals (Padilla, 2019).

The utilisation of Artificial Intelligence (AI) technology has transformed various sectors, including education, where it has been increasingly utilised in ODL systems to enhance the teaching and learning processes (Chen et al., 2020; Shen et al., 2021). The acknowledgement of the potential for

AI adoption in ODL to improve students' academic performance through personalized learning experiences is widespread (Allam, Hassan, Mohideen, Ramlan, & Kamal, 2020). However, the precise impact of AI adoption on academic performance in ODL and how it differs based on factors such as gender and regional disparities between developing and advanced countries is still uncertain. Therefore, further research is required to investigate this matter. Some studies have focused on exploring factors influencing student persistence in ODL, identifying both success factors and challenges faced by students in this mode of learning and proposing strategies for enhancing student persistence based on their findings (Au, Li, & Wong, 2018), the direct impact of AI adoption on academic performance remains largely unexplored.

Assessment in ODL not only serves as a means of grading and certifying students but also plays a critical role in their learning improvement and monitoring the effectiveness of academic programs, enabling the adoption of appropriate strategies to achieve institutional objectives (Koneru, 2017). In a recent study conducted during the COVID-19 pandemic, Libasin et al. (2021) compared the influence of different learning styles on students' academic performance between synchronous and asynchronous online learning in a Malaysian university. The findings revealed a positive impact of synchronous online learning on students' academic performance compared to asynchronous online learning. However, it is important to recognize the impact of AI adoption on academic performance. The variability of AI is contingent upon the precise context and manner of its implementation within ODL (Shen et al., 2021). Therefore, further research is necessary to delve into the effects of AI adoption on academic performance in ODL, considering the potential differences that may arise based on gender and regional disparities.

ODL is being increasingly adopted to expand access to education and enhance the development of digital skills, leveraging the opportunities presented by digital technologies. Within this context, Artificial Intelligence (AI) is an emerging field with numerous applications, including education. Machine learning algorithms, natural language processing, and computer vision are widely used in AI adoption in ODL to analyze student data, provide personalized learning experiences, and optimize educational content delivery (Valentin et al., 2022; Mathew & Chung, 2021). These methodologies have been instrumental in understanding student perceptions and enhancing the implementation of ODL amidst the COVID-19 pandemic (Mathew & Chung, 2021). For example, Machine learning algorithms have been widely used to predict student academic performance based on historical data and learning patterns. Various studies have demonstrated the effectiveness of machine learning techniques in this context. For instance, Yağcı (2022) compared the performances of different machine learning algorithms such as random forests, nearest neighbour, support vector machines, logistic regression, Naïve Bayes, and k-nearest neighbour to predict students' final exam grades.

Similarly, Livieris et al. (2018) applied supervised learning algorithms to develop accurate models for predicting student characteristics that influence their behaviour and performance. Onyema et al. (2022) and Buenaño-Fernández et al. (2019) also utilized machine learning algorithms to forecast students' academic outputs and predict the final grades of students based on their historical performance, respectively. Predicting academic performance through machine learning algorithms, particularly support vector machines (SVMs), is a notable area of AI research in education, specifically in ODL environments. This is the first study to look into the impact of AI adoption on academic performance in ODL settings using SVM. Furthermore, this study adds to the small body of literature addressing this current and critical issue related to Africa.

AI within ODL environments offers educators and institutions a comprehensive opportunity to enhance educational delivery. This integration necessitates a significant transformation in curriculum design and teaching methodologies, highlighting the critical importance of AI tools in contemporary educational scenarios. Togaibayeva et al. (2022) discuss the transformative potential of embedding AI technologies within educational frameworks, showcasing the broad possibilities for innovation. Concurrently, Sakibayev et al. (2019) provide evidence of the academic advantages stemming from the application of mobile technology in database courses, demonstrating clear, positive impacts on student achievement and success.

The journey toward adopting AI in education is complex, requiring a holistic view that encompasses a range of considerations—from technological advancements to socio-political, economic, cultural, and ethical dimensions. This comprehensive approach is supported by the work of Namoun & Alshanqiti (2020), Tait & Godfrey (2001), Shen (2023), Oyedeji et al. (2020), and Babić (2017), whose research collectively deepens our understanding of AI's advantages and limitations within educational contexts. As AI in education evolves rapidly, its capacity to fundamentally transform teaching and learning practices becomes increasingly evident. The development of predictive models, such as those utilizing Support Vector Machines (SVMs), to gauge the impact of AI adoption on student academic performance in ODL exemplifies just one avenue through which AI can significantly enhance educational outcomes. This innovative approach not only aligns with the broader trajectory of educational technology but also serves as a testament to the potential of AI to facilitate a more adaptive, personalized learning experience for students across diverse learning environments.

1.2 Statement of the problem

Despite the rapid adoption of AI in ODL, there is a critical gap in understanding how AI impacts academic performance. Existing research lacks a comprehensive framework for predicting these effects, leaving educators and institutions uncertain about how to best leverage AI to improve learning outcomes (García-Martínez et al., 2023; Alonso et al., 2021). This gap hinders the ability to make data-driven decisions that optimize AI's benefits in educational settings.

A key issue is the absence of studies that address the moderating role of gender and the contextual differences between developed and developing countries. These factors significantly shape how students interact with AI technologies, yet their impact on academic performance remains underexplored. For instance, gender may influence technology adoption and learning engagement, while students in developing countries face unique challenges such as limited access to AI tools (UNESCO, 2022; Yannier et al., 2021). This research tackles these gaps by developing a predictive framework using Support Vector Machine (SVM) to assess the impact of AI on academic performance in ODL systems. Crucially, it investigates how gender and contextual factors in both developed and developing countries affect this relationship. By addressing these nuances, this study provides actionable insights to optimize AI use in diverse educational contexts, making it a timely and necessary contribution to the field.

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1.2.1 Research Questions

The following are the research questions for the study:

I. What are the requirements for adopting AI in Open Distance Learning (ODL) (Dua, 2021)?

II. How can a process model that incorporates AI requirements in ODL be designed?

III. How can a research model be designed to incorporate factors of AI and student academic performance?

IV. How can machine learning models be developed with impact factors of AI adoption and student academic performance (Namoun & Alshanqiti, 2020)?

V. How can machine learning models of AI adoption and student academic performance be evaluated to determine the level of accuracy (Valentin et al., 2022)?

1.2.2 Research Hypothesis

The following are the research hypotheses for the study:

I. Comprehensive requirements of AI adoption in ODL would enhance student academic performance.

II. The design of a process framework would enhance the understanding of AI adoption in ODL.
III. The factors of AI adoption have a significant impact on student academic performance.
IV. The developed machine learning models would predict the impact of AI adoption on ODL students' academic performance.
V. The evaluation of the machine learning models would have a significant impact on the model's accuracy.

1.3 Aim of the study

This research aims to develop a process framework for predicting the impact of artificial intelligence adoption on students' academic performance in Open and Distance Learning (ODL) using a support vector machine.

1.4 Specific objectives

The specific objectives are to:

I. To develop a process framework incorporating the factors identified from the requirements to enhance understanding of AI adoption in ODL.
II. To develop a research model comprising the factors of AI adoption and student academic performance in ODL.
III. To develop a machine learning model to predict the impact of the identified factors of AI adoption on student academic performance.
IV. To evaluate the machine learning models to establish the level of accuracy.

1.5 Scope of the Study

The scope of the study includes:

I. **Target population:** The research focuses on students in Open and Distance Learning (ODL) systems currently enrolled in courses using AI-based interventions in Canada and Nigeria.
II. **Variables:** The study examines the impact of AI adoption on students' academic performance in ODL systems, focusing on factors such as student engagement, course design, and the effectiveness of AI-based interventions.
III. **Methodology:** The research designs a process-based framework and implements the framework using a Support Vector Machine (SVM) algorithm to predict AI adoption's impact on academic performance in ODL systems. The research methodology strongly emphasises assessing Moodle's AI capabilities, given its prominence and comprehensive utilization in ODL settings.

Moodle's AI tools are grounded in literature as the most evaluated AI solutions for fostering AI adoption in educational contexts, making them an essential focus for this research.

IV. **Data Collection:** Data are systematically gathered via surveys distributed to a sample of students in ODL systems, with questions tailored to gauge the utility and impact of Moodle's AI tools on their learning outcomes.

1.6 Significance of the Study

This research makes a significant contribution by developing a predictive framework that Open and Distance Learning (ODL) institutions can adopt to assess the impact of AI integration on students' academic performance. It addresses a critical gap in the existing literature by providing a comprehensive tool for ODL stakeholders, enabling them to evaluate both the benefits and potential drawbacks of AI adoption in their unique contexts. The framework is designed to predict academic outcomes by incorporating key AI adoption factors, as well as moderating influences such as gender and geographical differences, which have been underexplored in prior studies.

By applying a Support Vector Machine (SVM) model, this study provides a novel approach to forecasting academic performance in ODL settings. The model accounts for complex interactions between AI adoption factors and performance, offering insights that can inform policy decisions and educational strategies. Additionally, this framework can be applied across different educational disciplines, broadening its applicability beyond ODL environments.

The study's practical significance lies in its potential to assist educators and policymakers in making data-driven decisions about AI's role in improving academic outcomes. The theoretical contributions include advancing our understanding of AI's impact on learning environments, particularly in developing countries, where infrastructural constraints play a significant role. Methodologically, the research introduces an innovative process-based framework combined with predictive analytics, creating a scalable and replicable tool for evaluating AI's effects in education.:

1.7 Definition of Terms

In the context of this research, it is essential to clarify and define specific terms to ensure a unified understanding and to avoid ambiguities. Here are the definitions for the critical terms used throughout the thesis:

I. **Artificial Intelligence (AI):** Refers to the simulation of human intelligence processes by machines, especially computer systems. These processes include learning, reasoning, and self-correction.

II. **Open and Distance Learning (ODL):** A mode of education that caters to learners who might not be physically present in traditional classroom settings. It often leverages technology to deliver content and facilitate communication.

III. **Support Vector Machine (SVM):** A supervised machine learning algorithm that can be employed for both classification or regression tasks. It functions by finding a hyperplane in an N-dimensional space that distinctly classifies the data points.

IV. **Unified Modeling Language (UML):** A standardized modelling language can visualize a system's architectural blueprints, including activities, actors, business processes, and system components.

V. **Dataset:** A collection of data, typically organized in tabular form, where each row represents an instance and columns represent the attributes of the instance.

VI. **Validation:** The process of evaluating a system or component during or at the end of the development process to determine whether it satisfies the specified requirements.

VII. **Research Methodology:** A systematic way to solve a problem. It is the science of studying how research is conducted scientifically.

VIII. **Literature Review:** An evaluation of existing research related to the topic. It helps identify gaps, contradictions, parallels, and complements in the literature.

IX. **Performance Metrics:** Quantitative measures used to assess the performance of algorithms or models.

Each term, as defined above, serves as a foundation for the discussions and analyses that follow in the thesis. Understanding these terminologies aids in comprehending and appreciating the research's depth and implications.

1.8 Organization of the Thesis

The thesis has been meticulously organized to provide a comprehensive and coherent understanding of the study's progression. Chapter 1, titled "Introduction," offers a contextual backdrop, setting the stage for the research by defining the problem, outlining the overarching intent, specific goals, boundaries, and significance, while providing essential terminologies for clarity. Chapter 2 reviews previous studies on AI adoption in ODL and gives literature on subjects that include the impact of AI on academic performance, AI-driven personalized learning, and the use of Support Vector Machines (SVM) for predictive modeling in education. It also discusses theoretical frameworks and provides a consolidated meta-analysis to identify gaps and patterns from reviewed studies. Chapter 3 describes the empirical study carried out. This includes the development of a process framework for predicting academic performance, data collection from ODL students, model implementation using SVM and Structural Equation Modeling (SEM), and the evaluation of moderating factors such as gender and geographical context. The chapter also elaborates on the use of Unified Modeling Language (UML) to visualize the system's architecture and discusses performance metrics used to validate the model. Chapter 4 presents and discusses the implications and significance of results obtained, focusing on the predictive accuracy of AI models in assessing academic performance in ODL settings and their potential for optimizing educational strategies. The results are supported by quantitative measures, visual aids such as charts and graphs, and comparisons of the AI models' outcomes with traditional educational technologies to assess their effectiveness. Finally, Chapter 5 summarizes the study and concludes with suggestions for future research, including refining the models, extending the framework to other educational environments, and offering practical advice for educators, policymakers, and technologists on optimizing AI deployment in learning environments to foster more equitable, efficient, and engaging educational experiences.

1.9 Limitations of the Study

The limitations of this study are important to consider when interpreting the findings. First, the generalizability of the results may be limited, as the study focuses on a specific population of students in ODL systems, which may not fully represent all ODL contexts. Additionally, the sample size, while comprehensive enough for the analysis conducted, may still limit the broader applicability of the findings, particularly in diverse educational settings or regions. Another limitation is the reliance on self-reported data from students, which introduces the potential for social desirability bias. This means that students may have responded in ways they perceived as favorable rather than completely reflecting their true experiences or opinions. Despite these limitations, the study offers valuable insights into the relationship between AI adoption and academic performance in ODL environments, and it serves as a foundation for future research in this area. Future studies could address these limitations by expanding the sample size, including diverse populations, and utilizing more objective data collection methods.

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CHAPTER TWO
LITERATURE REVIEW

2.1 Preamble

Integrating AI in education has unveiled unprecedented opportunities for the enhancement of students' academic achievements. Specifically, ODL has experienced a notable increase in the application of AI to optimize both the learning experience and educational outcomes. Assessing the ramifications of AI integration on students' academic performance within ODL is of paramount significance for educational institutions, policymakers, and scholars alike. The objective of this chapter is to present the theoretical framework, a methodical review of pertinent literature, and an examination of related scholarly works to investigate and evaluate existing research concerning the specified subject matter. Through the adoption of a systematic and exhaustive methodology in the literature review, this analysis aims to discern the principal factors affecting AI adoption, investigate the predictive efficacy of SVM in evaluating the influence of these principal factors on students' academic performance, and reveal the impact of moderating variables such as gender and regional differences that may affect this influence.

Through a comprehensive exploration of esteemed databases, including Web of Science, Scopus, Google Scholar, and an array of pertinent articles published from 2015 to 2023, a systematic review of relevant literature and an examination of related works were conducted. The chosen articles underwent a meticulous assessment, emphasizing their coherence with the research inquiries and the rigour of the research methodologies utilized. Only peer-reviewed articles authored in English were deemed acceptable to ensure the dependability and trustworthiness of the findings. By integrating the insights derived from the selected articles, this systematic review of pertinent literature and the examination of related works aspires to furnish insightful perspectives regarding the procedural framework for forecasting the influence of AI adoption on students' academic performance in ODL employing SVM. The results of this review have the potential to enhance the integration of AI within ODL environments, guide decision-making processes for educational institutions, and facilitate further research within this swiftly advancing domain.

This systematic literature review is anticipated to shed light on the existing knowledge gaps, offer recommendations for future research, and provide a comprehensive understanding of the factors influencing the impact of AI adoption on students' academic performance in ODL. Ultimately, this review aims to contribute to the ongoing discourse on leveraging AI technologies to optimize the educational experience and outcomes for distance learners. This chapter addresses the following:

- **Theoretical Framework**
    - Technology Acceptance and Adoption Models
    - Support Vector Machine (SVM) approach
    - Conceptual framework of the study
    - Theoretical assumptions of the study
- **Review of Relevant Literature**
    - Factors Driving AI Adoption in ODL
    - Impact of AI Adoption on Academic Performance in ODL
    - Predicting Academic Performance Using SVM
    - Moderating Factors: Gender and Regional Differences
- **Review of Related Works**
- **Summary/Meta-Analysis of Reviewed Related Works**

2.2 Theoretical Framework

The exponential progression in artificial intelligence (AI) and its integration into education has generated significant interest among researchers. One crucial aspect is the impact of AI adoption on students' academic performance, particularly in the context of Online Distance Learning (ODL). This study aims to develop a process framework utilizing a Support Vector Machine (SVM) to predict the impact of AI adoption on students' academic performance in ODL. The theoretical framework is the cornerstone of any research, laying the foundation for interpreting the dynamics and outcomes of the study. In the context of this present work, the theoretical framework is instrumental in guiding the exploration and analysis of critical components such as AI adoption factors, moderating factors, and the outcome variable of students' academic performance.

This study integrates various theories and models to investigate the impact and adoption of AI in Open and Distance Learning (ODL) environments. The Technology Acceptance and Adoption Models primarily utilized include the TAM or the Technology Acceptance Model, UTAUT or the Unified Theory of Acceptance and Use of Technology, and the D&M Model or Information Systems Success. These models offer valuable insights into students' acceptance and utilization of AI in the ODL framework. They highlight the significant roles played by factors such as social influence, perceived ease of use, and perceived usefulness in determining the effective use and adoption of AI technology.

The Information Systems Success (D&M Model) is a foundation for understanding the factors contributing to AI adoption's success in ODL. It focuses on system quality, information quality, service quality, and user satisfaction, offering a comprehensive perspective on the effectiveness of integrating AI in ODL settings. By examining these theories, a comprehensive understanding of the complex dynamics involved in AI adoption in ODL and its impact on student performance can be gained. Applying the Support Vector Machine (SVM) algorithm aims to predict and analyse the relationships between AI adoption, ODL environments, and student outcomes. This predictive capability allows us to assess the potential of AI in enhancing educational experiences and outcomes in ODL. Utilizing these theories and models aims to provide valuable insights for educators, institutions, and policymakers seeking to leverage AI in ODL effectively. This research contributes to the broader understanding of how AI adoption can positively influence student performance and establish a more effective and personalized learning environment in the ODL landscape.

Finally, the principles underlying the SVM algorithm provide the technical underpinning for constructing the predictive model. This tool forecasts academic performance based on AI adoption and associated factors. The theoretical framework of this study intertwines a series of complex theories and models to form a coherent, insightful, and effective tool for predicting the impact of AI adoption on students' academic performance in ODL using SVM.

2.2.1 Technology Acceptance and Adoption Models

For an organization to successfully adopt modern technologies, it is important to understand the factors influencing their adoption thoroughly. This knowledge is crucial for effective planning and implementation, as it allows the organization to minimize internal and external pressures. By adopting modern technologies in a planned and strategic manner, organizations can ensure a smoother transition and maximize the benefits gained from using these technologies (Javaid et al., 2022; Birajdar & Vasudevan, 2022). Therefore, the primary goal of this review is to review different technology acceptance methods and identify the most effective technology acceptance method or combination of methods that are used in evaluating the factors that influence AI adoption in ODL settings. This section focuses on the theoretical frameworks that aim to understand and explain individuals' acceptance and adoption of new technologies. It discusses the models that provide valuable insights into the factors influencing individuals' attitudes and intentions towards adopting and using a particular technology. By examining users' perceptions, beliefs, and behaviours, TAAMs help researchers and practitioners understand how technology can be effectively introduced and integrated into various domains, including education. These Technology Acceptance and Adoption Models provide valuable frameworks for understanding and predicting users' acceptance and adoption of technologies in various contexts, including education. By considering factors such as perceived usefulness, ease of use, social influence, and individual beliefs, these models assist in designing strategies and interventions to promote the successful adoption and implementation of educational technologies, such as artificial intelligence, in educational settings.

Technology acceptance model (TAM)

The technology acceptance model is one of the most important models for how people accept new technology. An individual's intention to use new technology is primarily shaped by the perceived ease of use (PEOU) and the perceived usefulness of the technology (PU). The likelihood of an older adult learning digital games depends on their perception of the games. If they believe learning how to use digital games will be too difficult or a waste of time, they will be less likely to adopt this technology. However, if they believe digital learning games will provide much-needed mental stimulation and be easy to understand, they will be more likely to want to learn how to use digital games. While TAM has been criticized frequently, it remains a practical general framework consistent with several studies into the factors influencing older adults' willingness to use new technology (Charness & Boot, 2016). This model's emphasis on the potential user's perceptions is crucial. Figure 2.1 depicts TAM's original theoretical framework.

The model shows that behavioural intention (BI) determines the actual use of the system (AU), and BI is jointly and directly determined by one's attitude toward using the system (ATT) and one's PU. PU and PEOU have an impact on attitude as well. The inquiry centred on the utilization of the extended Technology Acceptance Model (TAM) to investigate how four factors influence Home Economics (HE) teachers' behavioural intention (BI) to use the Internet as a teaching tool, namely Internet attitude (IA), perceived ease of use (PEOU), and perceived enjoyment (PE), perceived usefulness (PU). The findings indicated that HE teachers' BI positively correlates with IA, PU, PEU, and PE (Phua, Wong, & Abu, 2012). This study employs the constructs of the proposed research model (PEOU, PU, BI, ATT, and PE).

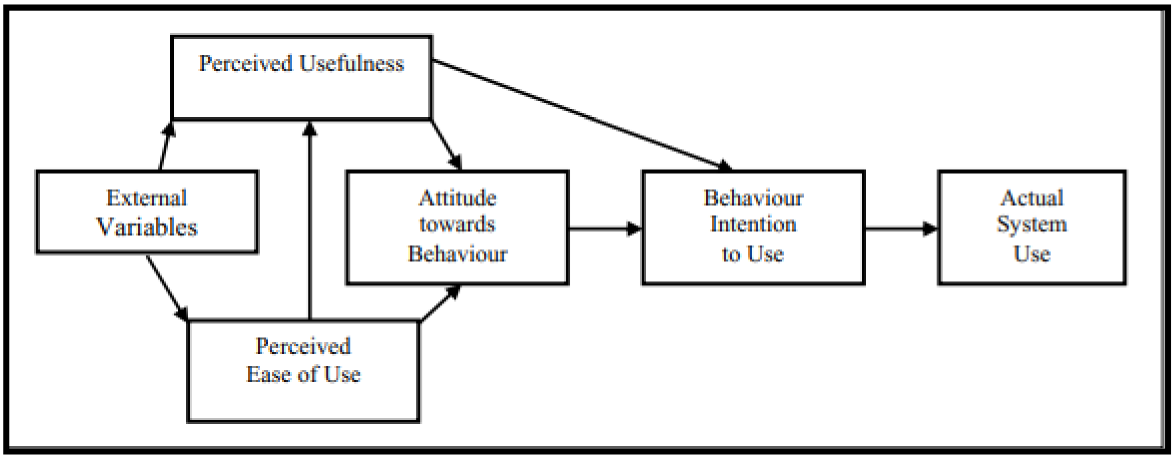


Figure 2.1 Original Technology Acceptance Model (TAM) Source: (Phua, Wong, & Abu, 2012)

Information Systems Success (D&M Model)

Intelligent systems cost much money and take time and work to set up. So, researchers and practitioners are always trying to figure out the most important factors that affect how these systems are used and how successful they are. According to (Sabeh et al., 2021), the DeLone and McLean (D&M) success model is one of the most common ways to study technology success. Many scholars have added to and improved the original D&M model or pointed out problems. The DeLone and McLean (D&M) information systems (IS) success model aims to give a complete picture of IS success by figuring out and explaining the relationships between the most critical success factors. According to (Ojo, 2017), the model provides six interconnected dimensions of IS success.

These are system quality, information quality, service quality, (intentional) use, user satisfaction, and net benefits. Numerous IS studies have used the D&M model and confirmed its validity. For example, Hospital information systems in developing countries were the focus of the research work by Ojo, 2017, which is an adaptation of the well-known DeLone and McLean information system success model. It was found that the quality of the system and the frequency with which it is used are significant indicators of a thriving hospital information system. This present study considers system quality and user satisfaction alongside other constructs from other technology acceptance models.

The UTAUT, or Unified Theory of Acceptance and Use of Technology

The UTAUT has gained significant attention from scholars in the technology acceptance field, according to Yakubu and Dasuki (2018). This is attributed to UTAUT's holistic framework facilitating a nuanced comprehension of the factors influencing technology adoption and usage. Consequently, UTAUT has become a widely used theoretical framework for research on technology adoption. The hedonic motivation, price value, and habit are the three additional constructs taken into consideration by the UTAUT2 model, which is an updated version of the framework used initially for the UTAUT model. The original UTAUT model contained four variables: facilitating conditions, performance expectation, effort expectation, and social influence (SI). Yakubu and Dasuki (2018) researched higher education students in Nigeria based on the UTAUT model. They found that the promotion conditions and behavioural intention were critical factors affecting their use of educational technology. Ameri et al. (2020) used a modified UTAUT2 questionnaire to survey pharmaceutical students. The results showed that social influence (SI) and performance expectancy (PE) positively affected behavioural intention. Almaiah et al. (2019) used the UTAUT model to explain why higher education students accepted a mobile learning system. They found that the main reasons were perceived information quality and perceived security. This present study considers facilitating conditions, social influence (SI), and other constructs from other technology acceptance models.

2.2.2 Support Vector Machine (SVM)

The Support Vector Machine (SVM) is a powerful machine learning algorithm that has gained popularity and success in various domains, including classification and regression tasks. SVM is based on the theoretical foundations of statistical learning theory and optimization techniques (Yang et al., 2023). This theoretical framework provides a solid basis for understanding the principles and concepts underlying the SVM approach. Here, the theoretical foundations of SVM as a machine learning algorithm are explored. The principles and mathematical concepts underlying SVM's ability to predict and classify data will be examined in relation to its application in predicting the impact of AI adoption on students' academic performance in ODL.

I. Statistical Learning Theory

Statistical Learning Theory forms the basis of the SVM approach. It focuses on the analysis of data to make predictions or decisions. The key idea behind statistical learning theory is to find a function that can accurately generalize from observed data to unseen instances. SVM leverages statistical learning theory to construct a decision boundary that maximizes the margin between different classes, aiming to achieve better generalization performance (Yang et al., 2023).

II. Linear Separability and Kernel Trick

SVM is based on the assumption that the data points of different classes can be separated by a hyperplane in a high-dimensional feature space. This assumption is known as linear separability. However, the data may not be linearly separable in the original feature space. The kernel trick transforms the data into a higher-dimensional space where linear separability can be achieved. The choice of appropriate kernel functions, such as linear, polynomial, or radial basis function (RBF), plays a crucial role in SVM's performance (Ramus et al., 2023; Singam et al., 2023; Rukhsar et al., 2022).

III. Margin Maximization and Support Vectors

The SVM algorithm seeks to identify the hyperplane that optimizes the margin separating the support vectors, which represent the data points nearest to the decision boundary. The margin represents the separation between different classes and provides a measure of robustness against noise and outliers. By maximizing the margin, SVM promotes better generalization and improved classification accuracy (Petrova & Bojikova, 2022; Rizwan et al., 2021).

IV. Convex Optimization

SVM involves solving a convex optimization problem to find the optimal hyperplane. Convex optimization techniques, such as quadratic programming, are utilized to determine the hyperplane parameters that minimize the classification error and maximize the margin. The convexity of the optimization problem guarantees the solution's global optimality and ensures the SVM algorithm's efficiency (Wang et al., 2021; Piccialli & Sciandrone, 2022).

V. Regularization and Control of Overfitting

Overfitting is a common issue in modelling where a model may perform well on the training data but fails to generalize to novel, unseen data. To address this issue, Support Vector Machines (SVMs) utilize regularization techniques such as the C parameter, which controls the balance between achieving a larger margin and minimizing the classification error. Regularization helps prevent overfitting by introducing a penalty for misclassified instances and balancing the complexity of the model (Ghojogh & Crowley, 2019; An et al., 2020).

The theoretical framework of the Support Vector Machine (SVM) approach is grounded in statistical learning theory, optimization techniques, and convex optimization. By leveraging the concepts of linear separability, margin maximization, support vectors, and convex optimization, SVM provides a robust and efficient method for classification and regression tasks (Chopra & Khurana, 2023; Sun, 2016). Understanding the theoretical foundations of SVM is essential for effectively utilizing and interpreting the results of this powerful machine-learning algorithm. The principles and mathematical concepts underlying SVM contribute to its predictive ability. SVM's performance in various domains, such as breast cancer prediction, compressor performance prediction, and academic performance prediction, indicates its effectiveness as a machine learning algorithm based on statistical learning theory and optimization techniques (Yang et al., 2023).

2.2.3 Conceptual Framework

The conceptual framework outlines the fundamental components and interrelations in forecasting the influence of AI adoption on the academic performance of students. This framework encompasses three essential dimensions: Factors Influencing AI Adoption, Moderating Variables including Gender and Regional/Geographical Disparities, and the Resultant Variable.

I. Factors Influencing AI Adoption

The factors influencing AI adoption within the realm of Online Distance Learning (ODL) encompass a diverse array of elements that significantly affect the integration and utilization of AI technologies. These determinants illuminate the complex interactions between AI systems and essential stakeholders, including educational institutions, instructors, and learners. As posited by Chen et al. (2020), AI platforms must be congruent with the objectives, ethical standards, and requirements of the learning community, providing unique benefits compared to conventional educational methodologies, such as tailored learning experiences and improved engagement. Simultaneously, factors related to AI preparedness evaluate an institution's technical capabilities, cognitive readiness, and the existing infrastructure for AI integration. Moreover, an institution's flexibility, in conjunction with factors such as technology accessibility, motivation, and perceived usefulness, plays a crucial role in shaping the landscape of AI adoption. Such elements can be systematically assessed through surveys, facilitating a thorough quantitative investigation of AI adoption (Phua, Wong, & Abu, 2012).

II. Moderating Factors, Including Gender and Regional Variations

The moderating factors denote those elements that influence the effectiveness of AI adoption factors on students' academic performance in ODL. The impact of AI adoption factors is moderated by variables such as gender and regional/geographical variations, thereby affecting the relationship between AI adoption and academic performance. Acknowledging these moderating factors is essential as they provide critical insights into how diverse demographics may react differently to AI adoption in ODL, ensuring a comprehensive understanding of the dynamics at play.

III. Dependent Variable

The dependent variable in this study pertains to the academic performance of students, which can be assessed through various indicators such as final grades, assessment scores, or cumulative GPA. This academic performance functions as the dependent variable, which is forecasted based on the factors of AI adoption and the moderating elements.

IV. Support Vector Machine (SVM)

The support vector machine (SVM) is an algorithm in machine learning that is amenable to deploying within the framework of predicting students' academic performance by identifying artificial intelligence (AI) adoption factors and moderating factors. SVM has shown promising results in predicting students' achievements, engagement, and performance in online learning settings, and it achieves this by utilizing a classification or regression approach to construct a predictive model. This model can categorize students into different performance classifications or estimate their performance levels (Tomasevic et al., 2020; Ayouni et al., 2021).

The conceptual framework (Refer to Figure 2.2) asserts that factors influencing the adoption of AI have a significant impact on students' engagement with AI in ODL, thereby subsequently affecting their academic outcomes. The moderating variables act as intermediary constructs, facilitating the prediction and clarification of the correlation between AI adoption and academic performance. The SVM algorithm develops a predictive model aimed at forecasting students' academic success based on the identified factors and moderating elements.

By taking into account the factors related to AI adoption, the moderating variables, and harnessing the capabilities of the SVM algorithm, the proposed conceptual framework outlines a systematic approach to investigate the ramifications of AI adoption on students' academic performance within the ODL environment. This framework aspires to enhance our comprehension of the interrelationship between AI adoption and academic results in the context of ODL. The insights obtained from this inquiry may prove instrumental in devising effective strategies for the integration of AI in educational settings and in optimizing students' learning experiences within online platforms.

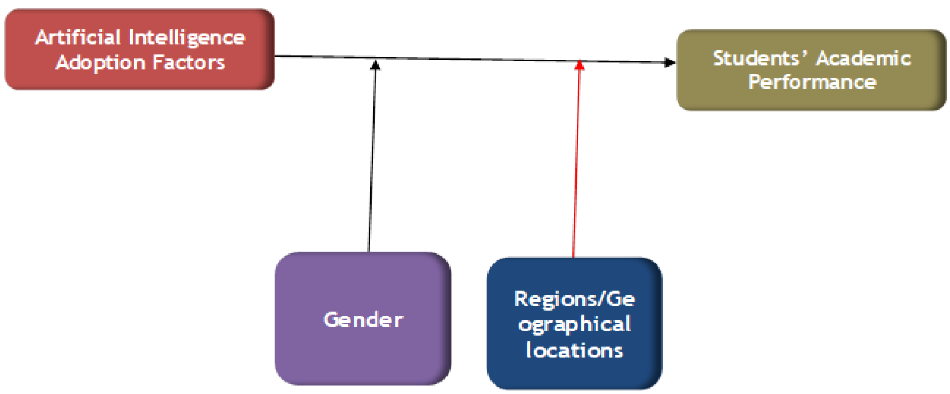


Figure 2.2 Conceptual Framework (Source: Author's work)

2.2.4 The Theoretical Assumptions of the Study

The theoretical assumptions of the study include the following:

- **Technological Determinism:** This study assumes that adopting AI technology can directly and significantly impact students' academic performance in an ODL (Open and Distance Learning) environment.

- **Adoption Factors Matter:** The research posits that certain adoption factors (e.g., acceptance, access, motivation, perceived usefulness, and ease of use) play a critical role in the successful integration and utilization of AI in education.
- **The Moderation Effect:** The study presumes that gender and regional/geographical differences can moderate the relationship between AI adoption and students' academic performance.
- **Measurability:** The research assumes that both the AI adoption factors and students' academic performance can be accurately measured using available tools and techniques (e.g., validated scales, surveys, and grade point averages).
- **Predictability:** A key assumption is that the student's academic performance can be predicted using SVM, a machine learning algorithm based on AI adoption factors and moderating factors.
- **Universal Applicability of AI:** The study assumes that AI technologies can be effectively used in various educational contexts and disciplines within ODL.
- **Technological Readiness:** It assumes that the technology infrastructure in the ODL environment is ready to accommodate the use of AI technologies.
- **Causal Relationships:** The research assumes that the relationships between AI adoption factors, moderating factors, and academic performance are causal, not merely correlational.
- **Transferability:** The study assumes that the results and findings are generalizable and can be transferred to other similar educational contexts.
- **Technological Neutrality:** The study assumes that AI is a neutral tool, the effects of which are determined by how it is used in the ODL environment rather than the inherent qualities of the technology itself.

These assumptions form the theoretical backbone of the study, guiding its design, execution, and interpretation of results. It is important to remember that these assumptions would need to be scrutinized and tested as the study progresses to ensure the validity and reliability of the findings.

2.3 Review of Relevant Literature

AI offers numerous opportunities for Open and Distance Learning (ODL) institutions, specifically in addressing effective teaching and learning methods and exploring the advantages and limitations of computer-based systems in education (Liu & Huang, 2022). The flexibility and accessibility of ODL have encouraged more female students to study IT and computer science (Ogunsola-Bandele & Kennepohl, 2022). Integrating AI into distance education can profoundly impact instructional methods, guidance approaches, and educational content (Gao, 2022). By incorporating cutting-edge

AI technology into existing e-learning systems, personalized, adaptive, and intelligent services can be provided to students and educators alike (Tanjga, 2023). However, the full implementation of AI in education has not been fully realized, and successful AI applications in e-learning have yet to be widely adopted, especially in open-source learning management systems (Huang et al., 2021).

Kuleto et al. (2021) state that Artificial Intelligence (AI) and Machine Learning (ML) have their roots in data management and development processes. Integrating AI and ML into various industries, including education, is a groundbreaking trend. This integration enhances learning by customizing platforms and applications to meet student needs. Extensive research is underway to improve educational processes, making AI in Education a rapidly advancing field within the education sector. Developed countries have displayed significant interest in exploring the applications of AI in Higher Education, leading to a wealth of literature on this subject. AI and ML technologies enhance education by fostering student competence, facilitating group work, and providing easy access to academic resources. With the increasing prominence of AI tools, there is a growing emphasis on their utilization in educational settings to enhance students' learning performance.

In recent years, the adoption of AI has become widespread across various industries, including education. Integrating AI into Open and Distance Learning (ODL) has the potential to enhance student's learning experiences and improve their academic performance. However, there is a need to develop a process framework that can predict the impact of AI adoption on students' academic performance in ODL. This systematic literature review aims to identify relevant studies, synthesize their findings, and propose a process framework for predicting the impact of AI adoption on students' academic performance in ODL.

The systematic literature review followed a well-established methodology involving the identification of relevant studies, data extraction, and synthesis of findings (de la Torre-López, Ramírez, & Romero, 2023). The review focuses on several aspects of AI adoption in ODL, including the factors driving its adoption, the impact of AI adoption on students' academic performance, the use of a Support Vector Machine (SVM) for predicting this impact, and potential gender and regional differences in the effect of AI adoption on academic performance in ODL. The review followed a four-step process, as depicted in Figure 2.3:

I. Identification of relevant studies,
II. Screening of studies,
III. Eligibility/selection of studies, and
IV. Inclusion of studies and synthesis of findings.

A systematic search was performed using Google Scholar, Scopus, and Web of Science databases, as well as a snowballing approach, to conduct this review. A total of 700 studies were identified, of which 80 were selected for full-text screening. After the screening, 53 studies were included in the final selection. The studies were published between 2015 and 2023 and were conducted in different countries, including the United States, China, and India. The search terms used included "artificial intelligence adoption," "online distance learning," "academic performance," "support vector machine," "gender differences," and "regional differences." The inclusion criteria encompassed peer-reviewed articles published between 2015 and 2023, written in English, and directly relevant to the research questions. Articles not peer-reviewed, unrelated to the research questions, or published before 2015 were excluded. After an extensive literature search, 53 articles addressing the research questions were identified. The following research questions guide the systematic literature review:

I. What factors drive AI adoption in Online Distance Learning (ODL) settings?
II. How does AI adoption impact students' academic performance in ODL?
III. How can these factors be used to predict students' academic performance using the Support Vector Machine (SVM) approach?
IV. How do moderating factors such as gender and regional differences affect the impact of AI adoption on students' academic performance in ODL?

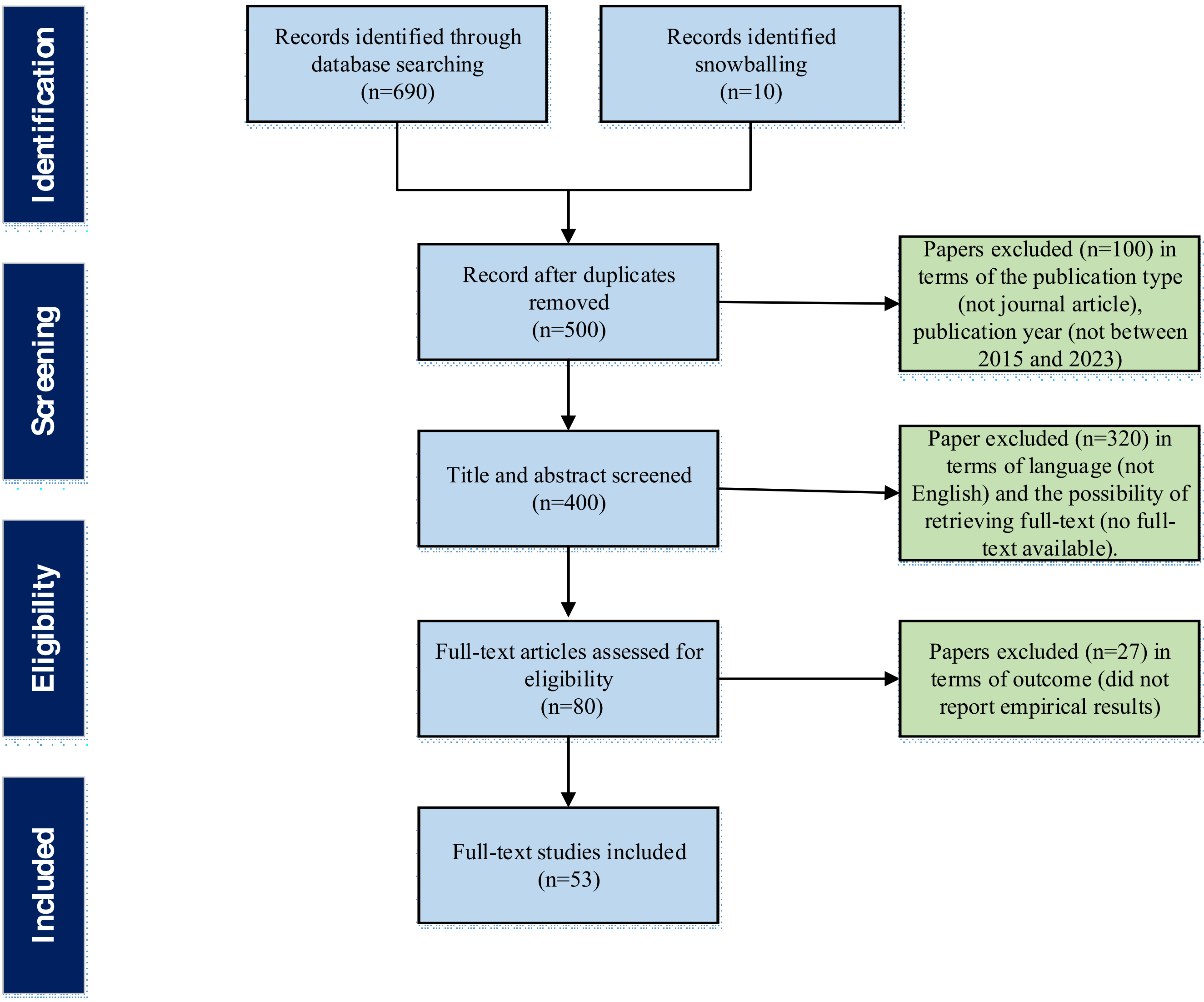


Figure 2.3 Systematic literature review of the impact of AI adoption on students' academic performance (Source: Author's work)

The prevalence of Artificial Intelligence (AI) is on the rise across multiple domains, including education. Specifically, AI adoption in online distance learning (ODL) settings offers several unique benefits and challenges. This review systematically examines the literature on this topic to explore the key factors driving AI adoption, the impact of these factors on academic performance, how these factors might be used to predict academic performance using a Support Vector Machine (SVM), and how moderating factors such as gender and regional differences can affect AI adoption's impact. The following four categories were employed in the systematic literature review to answer the research questions effectively:

I. Factors Driving AI Adoption in ODL
II. Impact of AI Adoption on Academic Performance in ODL
III. Predicting Academic Performance Using SVM
IV. Moderating Factors: Gender and Regional Differences

2.3.1 Factors Driving AI Adoption in ODL Settings

Research Question 1: What principal determinants propel AI adoption in Online Distance Learning (ODL) settings?

A comprehensive analysis was undertaken to discern the significant variables propelling the integration of Artificial Intelligence (AI) within Online Distance Learning (ODL) frameworks. Emerging from this study were several factors that played a pivotal role in driving this technological progression.

The leading technology acceptance theories, such as the Technology Acceptance Model (TAM), focus on ease of use and usefulness (Charness & Boot, 2016), the Information Systems Success (D&M Model), emphasizing system quality and user satisfaction (Sabeh et al., 2021), and the Unified Theory of Acceptance and Use of Technology (UTAUT), considering a broader framework including social influence (Yakubu & Dasuki, 2018), were reviewed. These theories offer a nuanced understanding of the factors affecting AI adoption in online distance learning (ODL) settings.

A primary catalyst of this trend is the potential for personalized and adaptive learning. The capacity of AI to customize educational paths to fit individual learners contributes to improved academic achievements and an uptick in student engagement (Bozkurt et al., 2021). Further facilitating this growth is adopting learning analytics, a tool that offers critical insights into student behaviours and learning styles. This amplifies the effectiveness of pedagogical feedback and refines teaching methodologies (Nguyen et al., 2020).

These conclusions are further substantiated by recent research. Studies by Almaiah et al. (2022) underscore the impact of enhanced academic outcomes, increased efficiency, cost-effectiveness, and tailored learning experiences on driving AI adoption. Furthermore, the research highlights the role of improved student engagement in promoting AI uptake in ODL contexts. Adding to this empirical evidence, Horowitz and Kahn (2021) affirm the importance of immediate feedback as a significant driving factor. Likewise, instructional quality, content relevance, motivation, and student relationships considerably influence student acceptance of ODL (Alam et al., 2022). From an organizational standpoint, compatibility, relative advantage, AI readiness, business process adaptability, and leadership have emerged as crucial for embracing AI (Kurup & Gupta, 2022).

At an individual level, perceived usefulness, performance expectancy, attitudes, trust, and effort expectancy shape AI technology's intention and actual usage (Kelly et al., 2022). Understanding these variables, therefore, offers invaluable insights into the broader landscape of AI adoption in ODL contexts. Despite some overlaps, the key factors driving AI adoption within ODL and conventional educational settings vary considerably. Within ODL frameworks, aligning AI systems with the goals, values, and needs of institutions and students plays a vital role. Other significant factors include comparative benefits offered by AI over traditional education methods, the level of AI preparedness, and the capacity of institutions to adapt their processes to accommodate AI (Chen et al., 2020). The emotional dynamics of learning, encompassing learning-related anxiety and the readiness for online interaction and collaboration, also play a critical role. Additionally, the impact of AI systems on knowledge absorption and online interaction enhancement is considered integral to their adoption (Almaiah et al., 2022).

In contrast, AI adoption in traditional learning environments is influenced by different factors, such as performance anticipation, attitudes towards AI, the level of trust in the systems, the effort expectancy, and the perceived applicability of the technology (Kelly et al., 2022). In summary, the driving factors for AI adoption in ODL scenarios are primarily centred on aligning AI systems with institutional and learner needs and the capacity to adapt to technological advances. On the other hand, adopting AI in traditional learning settings leans more towards these systems' perceived usefulness and ease of use.

2.3.2 Impact of AI Adoption on Academic Performance in ODL

Research Question 2: How does AI adoption impact students' academic performance in ODL?

The influence of certain factors on students' academic performance in Open and Distance Learning (ODL) can be examined by addressing the research question above. Extensive literature suggests that the application of AI in ODL settings has a significant positive correlation with improvements in students' academic achievements. This effect is particularly pronounced when AI systems are utilized for personalizing learning and delivering timely, pertinent feedback (Zhu et al., 2018).

Moreover, AI-powered tools, such as intelligent tutoring systems, can provide custom-tailored instructions addressing individual student needs, leading to a marked enhancement in learning outcomes (Lu et al., 2021).

Several studies have reviewed the effect of these factors on students' academic performance and have highlighted their beneficial influence on academic achievement. The conclusions drawn from these studies emphasize the following mechanisms through which AI adoption positively affects academic performance:

- Enhancement of learning outcomes
- Boosting student engagement
- Provision of tailored learning experiences (Ali et al., 2023)
- Availability of immediate feedback (Bertl et al., 2022)

This evidence underscores the transformative potential of AI in the ODL landscape, revolutionizing the learning experience and driving educational success.

The factors driving the adoption of AI in ODL settings can positively impact academic performance. Here are some specific ways in which these factors can influence academic performance in ODL:

I. AI performance prediction models can accurately predict and monitor student academic performance in online higher education (Ouyang et al., 2023; Khan et al., 2021). This predictive capability helps identify at-risk students and establish student-centred learning pathways.

II. The integration of AI and learning analytics can improve student learning in online engineering courses (Ouyang et al., 2023). Providing students with in-time and continuous feedback enhances their learning quality.

III. AI-enabled prediction models can help anticipate academic achievement in online education, aiding instructors in preparing and delivering more effective teaching and learning (Jiao et al., 2022; Cruz-Jesus et al., 2020). This allows instructors to tailor their approaches to suit individual student needs.

IV. Machine learning algorithms can monitor students' academic progress and alert instructors about students at risk of unsatisfactory results in a course (Khan et al., 2021). Timely interventions can then be taken to improve student performance.

V. Machine learning algorithms can achieve high prediction accuracy and forecast student enrollment, college admission, dropout rates, and the risk of failure and withdrawal in online courses (Cruz-Jesus et al., 2020). This helps institutions support student success and improve decision-making.

VI. The integration of AI and learning analytics can support instructors in making informed decisions to facilitate student-centred learning and enhance the knowledge-construction processes of student groups (Ouyang et al., 2023).

The factors driving AI adoption in ODL can positively impact academic performance by accurately predicting and monitoring student performance, improving student learning, identifying students at risk of unsatisfactory results, and supporting instructors' informed decision-making. These results emphasize the noteworthy capacity of artificial intelligence within open and distance learning to amplify academic achievements and generate a more efficient and individualized educational setting for students. However, it is important to note that implementing AI in ODL also presents potential disadvantages and challenges. Research has emphasized the potential drawbacks of implementing Artificial Intelligence (AI) in Open Distance Learning (ODL), with specific regard to students' academic performance (Almaiah et al., 2022). A fundamental observation is that learners' perceptions of AI can profoundly affect its success, indicating a necessity to lessen the anxiety associated with AI for better outcomes.

Notably, students and teachers share concerns about AI's role in education. They fear that overreliance on AI could unintentionally restrict students' chances for exploration and discovery (Seo, Tang, Roll, Fels, & Yoon, 2021). This concern is mirrored in their experiences, where many negative interactions with AI systems are rooted in misconceived expectations and misunderstandings about technology. Furthermore, adopting new technologies like AI often triggers anxiety, impeding their acceptance and use (Youmei Wang, Liu, & Tu, 2021). Another key concern is the risk of over-standardizing the learning process, which might diminish students' self-control in their learning paths. Although students acknowledge AI systems' potential aid, they also raise concerns that such standardized assistance could negatively impact their self-guided learning (Youmei Wang, Liu, & Tu, 2021).

Further inquiry is needed to comprehensively understand the impact of AI adoption on students' academic performance in ODL. While AI promises to enrich learning outcomes and promote personalized education, concerns remain regarding over-standardization, elevated anxiety, and potential adverse impacts on self-directed learning. A multifaceted challenge exists in deciphering the complex interplay of factors influencing AI adoption and its effects on academic performance. A comprehensive understanding of these factors and the development of appropriate frameworks will pave the way for effective and responsible use of AI in ODL, promoting educational success in the digital age. It is essential to develop a process framework that can predict the impact of AI adoption on students' academic performance in ODL, ensuring that it effectively enhances learning while addressing challenges related to over-standardization, anxiety, and self-directed learning. Such a process framework could provide an essential tool in anticipating and managing these outcomes, ensuring that AI's integration in ODL effectively enhances learning while addressing the associated challenges.

2.3.3 Predicting Academic Performance Using SVM

Research Question 3: How can these factors predict students' academic performance using the

Support Vector Machine (SVM) approach?

A plethora of research has been dedicated to applying Support Vector Machine (SVM) to predict student outcomes in online distance learning (ODL) environments. A notable example is a study by Mduma et al. (2019) that offers a holistic view of machine learning methodologies for predicting student dropout. It highlights using multiple machine learning models, including SVM, to predict student dropout and factor in demographics, academic records, and engagement levels. The study underscores the potential of machine learning as an identifier of at-risk students, providing an opportunity for targeted interventions to reduce dropout rates. Additionally, Tomasevic et al. (2020) suggest that SVM can effectively predict student performance when trained on relevant parameters like historical academic records, engagement metrics, and behavioural tendencies.

The potential of SVM in forecasting student performance has been revealed through further exploration, considering a variety of influencing factors. For instance, Ayouni et al. (2021) assessed the efficacy of machine learning algorithms for predicting student engagement in online learning environments. Their study found the SVM algorithm particularly effective in predicting engagement levels by analysing student interactions within the online learning platform. This suggests the potential of SVM as a tool to boost student engagement and improve overall learning outcomes.

Within online education, AI performance prediction models have demonstrated remarkable progress. They have been employed in online higher education to predict and monitor student performance by leveraging student learning data and machine learning algorithms (Ouyang et al., 2023). For instance, an AI-powered prediction model was developed to predict learning outcomes for students in online engineering education (Jiao et al., 2022). The integration of AI and learning analytics has sparked innovative pedagogical approaches. Such fusion offers educators a wealth of data to stimulate student-focused learning and strengthen knowledge-building within student cohorts. The insights obtained from this integration can significantly enhance the quality of online education (Ouyang et al., 2023).

The scope of AI extends beyond student learning to predict instructor performance. Xiao et al. (2021) proposed a model that comprehensively analyses numerical data associated with several teacher-relevant factors to assess instructor performance. This demonstrates the potential of AI in not only boosting student learning but also enhancing teaching methods. AI algorithms are vital in developing performance prediction models for online education. Machine learning, a subset of AI, is widely used to predict academic outcomes in digital learning environments (Jiao et al., 2022). By detecting intricate patterns within data, these algorithms can forecast student performance accurately. Evolutionary computation, another facet of AI, has been employed to develop models that predict student performance in online learning contexts (Jiao et al., 2022). This approach, which mimics the processes of natural evolution, can solve complex optimization issues, thereby increasing prediction accuracy. AI algorithms, particularly machine learning, contribute substantially to constructing AI performance prediction models, utilizing student learning data to forecast and monitor academic progress (Ouyang et al., 2023; Jiao et al., 2022). These models also assess instructor performance, showcasing AI's extensive role in online education.

The efficacy of AI algorithms in performance prediction models for online education can vary based on the specific algorithm applied. Our findings reveal that machine learning algorithms are extensively used to predict academic performance in online educational contexts (Ouyang et al., 2023; Jiao et al., 2022; Holicza & Kiss, 2023). Notably, evolutionary computation has been employed to construct predictive models, as demonstrated by Jiao et al. (2022), who developed a student performance prediction model using this technique. A comparative study by Holicza & Kiss (2023) evaluated the efficacy of different machine learning algorithms in predicting online and offline student academic performance, with the Random Forest algorithm exhibiting the highest accuracy. Among various AI algorithms, the SVM approach has shown promising results. It is more accurate than other machine learning algorithms in predicting student performance (Ouyang et al., 2023). These results underscore the necessity of selecting the most suitable AI algorithm to enhance prediction accuracy in online education models. AI algorithms offer substantial benefits in predicting student performance in online education. They facilitate the early identification of at-risk students, enabling preventive measures to improve performance (Ouyang et al., 2023).

Additionally, AI algorithms provide personalized recommendations to enhance academic performance, and by dissecting individual student performance data, these algorithms can create tailored strategies to improve learning outcomes (Ouyang et al., 2023). Combining AI and learning analytics provides educators with crucial data for informed decision-making, fostering student-centred learning and refining knowledge-building processes (Ouyang et al., 2023). Lastly, AI's predictive analytics capacity can analyse student performance data to anticipate potential issues and forecast future outcomes, empowering educators to address academic challenges and proactively provide targeted support to students (Kelly et al., 2023). In essence, AI performance prediction models provide substantial advantages in online education. They accurately predict and monitor student performance, aiding in identifying at-risk students and crafting student-centric learning pathways. They also equip educators with the necessary data to improve performance and make informed decisions. Furthermore, using different AI algorithms and their varying accuracy underscores the significance of choosing the most effective AI algorithm, like SVM, for precise performance prediction.

2.3.4 Moderating Factors: Gender and Regional Differences

Research Question 4: How do moderating factors such as gender and regional differences affect the impact of AI adoption on students' academic performance in ODL?

The research underscores the moderating role of factors like gender and regional disparities on the impact of AI adoption on students' academic performance in Online Distance Learning (ODL). For instance, notable discrepancies exist in the attitudes towards and usage patterns of AI-enhanced educational tools between male and female students (Gardner, Brooks & Baker, 2019). Additionally, regional variances, such as the availability of technological infrastructure and the prevailing cultural attitudes towards technology, can influence the effectiveness of AI in education (O'Dea & O'Dea, 2023). Kumar and Choudhury (2022) highlighted the issue of gender inequality within artificial intelligence. The development process of AI systems can inadvertently embed gender bias due to unconscious biases held by the algorithm developers. They may unknowingly transmit these socially ingrained biases to AI systems. This bias is exemplified in how current trends in machine learning reinforce age-old stereotypes about women, such as their perceived modesty, gentleness, and the need for protection. For instance, the majority of security robots are designed as male, while most service and sex robots are female.

Toplic (2021) emphasized that the growing ubiquity of AI carries profound implications. Barriers to accessing and using digital technologies, including AI, can hinder women and girls from leveraging opportunities in education, the economy, and society. Astonishingly, out of the world's 796 million illiterate individuals, over 66% are women. Furthermore, the majority of the world's 2.9 billion people without internet connectivity are women. Evidence shows that women are 25% less likely than men to possess digital proficiency for everyday tasks. This lack of equal access to digital technologies, including AI, obstructs women and girls' progress in economic, social, and educational domains. Therefore, understanding the factors driving gender differences in the adoption of AI-based applications in ODL settings is crucial for promoting gender inclusion and equality principles in the adoption of AI for sustainable education.

In conclusion, the systematic literature review indicates that AI is promising to enhance outcomes in Online Distance Learning (ODL). However, it is crucial to consider personal and regional differences that can influence its effectiveness. Ongoing research should continue to explore these differences and construct tactics to optimize the advantageous aspects of Artificial Intelligence in Open and Distance Learning. Further investigation is required to fully understand the influence of moderating factors, such as gender and regional disparities, on the impact of AI adoption on students' academic performance in ODL. The present research aims to investigate the specific impact of these moderating factors on students' academic performance within the context of Online Distance Learning.

Overall, this systematic literature review provides valuable insights into the driving factors behind AI adoption in ODL and their impact on students' academic performance. The use of support vector machine (SVM) as a predictive model and the development of process frameworks show promise in predicting the effects of AI adoption on academic performance. The findings suggest that AI adoption has the potential to improve learning outcomes, enhance student engagement, and provide personalized learning experiences in ODL. However, further research is needed to explore the moderating factors that influence the impact of AI adoption, such as gender and geographical location differences. It is also important to address the limitations of the reviewed studies, including small sample sizes and limited generalizability, in future research. This systematic literature review is a foundation for further investigations into the factors influencing AI adoption and its ramifications on student academic performance in ODL settings. The study's outcomes can inform the development of effective strategies for promoting the successful integration of AI in education. It is essential to continue advancing research in this field to unlock the full potential of AI in enhancing outcomes in Online Distance Learning.

2.4 Review of Related Works

The potential impact of AI on education as a whole has been discussed in several studies (Chen et al., 2020; Shen et al., 2021; Chaudhry & Kazim, 2021; Khare, Stewart, & Khare, 2018; and Tanveer, Hassan, & Bhaumik, 2020). However, Ouyang, Zheng, and Jiao (2022) note that there is still a need for more empirical research to test the actual effects of AI applications in online higher education. Allam, Hassan, Mohideen, Ramlan, and Kamal (2020) highlight the limited research that focuses on the direct impact of AI adoption on students' academic performance, particularly in the context of ODL systems. While some studies have explored the use of AI in education, they have predominantly centred on traditional classroom settings and have not fully addressed the distinctive characteristics of ODL systems. The study also suggests that further research is needed to understand how the various factors influencing AI adoption affect academic performance, specifically in ODL systems. The application of AI in educational settings presents numerous opportunities, particularly for ODL institutions. Given that ODL heavily relies on human-machine interactions, AI offers these institutions various avenues to address key aspects such as effective learning methods, teaching strategies, and the advantages and limitations of computer-based systems in education (Oyedeji, Salami, Folorunsho, & Abolade, 2020).

The study conducted by Allam, Hassan, Mohideen, Ramlan, and Kamal (2020) revealed a low level of self-directed learning and metacognitive online learning among undergraduate students, indicating the necessity for additional research to explore how artificial intelligence (AI) can support these areas. Tait (2014) emphasizes the need to reconfigure student support in the digital age, specifically in distance and e-learning, which involves understanding the impact of AI adoption. Chaudhary and Dey (2013) underscore the importance of diverse assessment techniques and methods in open and distance learning (ODL), including exploring AI's impact on assessment. Olivier (2016) investigates the influence of face-to-face contact sessions and virtual discussion forums on academic performance in ODL, further emphasizing the need for research to comprehend the impact of AI on academic achievement. Koneru (2017) discusses the significance of assessment in ODL for enhancing learning and monitoring academic program effectiveness, which necessitates understanding the impact of AI on assessment. Msweli (2012) recognizes ODL as an effective means of promoting educational equity, emphasizing the requirement for research on how AI can support this goal.

Furthermore, Khor (2014) analyzes student perception and adoption behaviour of ODL using the technology acceptance model, providing valuable insights into students' perspectives and adoption of AI in ODL. Rifin, Kadiran, and Bakar (2022) address the challenges faced by students and lecturers in transitioning from conventional lecture-based approaches to online distance learning, emphasizing the need for research on the impact of AI adoption on academic performance. Therefore, there is a clear need for further research to gain a comprehensive understanding of how AI adoption influences students' academic performance in ODL systems. These research endeavours contribute to advancing the integration of AI in education and its potential to enhance learning outcomes in ODL settings.

Therefore, the problem addressed by this research is the lack of a comprehensive framework that can predict the impact of AI adoption on academic performance in ODL systems. Given the increasing adoption of AI in ODL systems, there is a need to develop a process-based framework that can predict the impact of AI on academic performance. This research aims to develop a comprehensive process-based framework for predicting the impact of AI adoption on students' academic outcomes in Open and Distance Learning (ODL) using a Support Vector Machine (SVM), focusing on gender and regional differences. The main focus of this research is to design, validate, and implement the process framework, with the implementation phase involving the use of Support Vector Machine learning for prediction. Additionally, the study evaluated the efficacy of the implemented system. A dataset was collected from ODL students to facilitate the prediction process to ensure accurate and reliable results. The study identified the factors impacting AI adoption that influence students' academic performance. By accounting for gender and regional differences in the proposed framework, the study promotes inclusive and equitable quality education through AI in ODL, which aligns with the United Nations' Sustainable Development Goal 4. The findings help design and implement effective AI-based interventions to enhance students' academic performance in ODL systems. Additionally, the research contributes to advancing knowledge of AI and its impact on education, particularly in the context of ODL systems. The predictive process framework and model will offer the following benefits:

- **Forecasting and Planning with Standardization:** Gathering data directly from students provides immediate insights into their experiences with AI tools and the effects on their academic performance through statistical analysis. However, developing a predictive model for assessing the impact of AI adoption on academic performance offers distinct advantages. This approach allows for a broader understanding of AI's potential effects before widespread implementation, enabling educators and policymakers to make informed decisions, tailor educational strategies, and anticipate long-term outcomes. Predictive modelling extends beyond immediate feedback, providing strategic, scalable, and efficient insights for enhancing the integration of AI in educational settings. By forecasting the potential impact of AI tools before their widespread implementation, educators and policymakers can engage in better planning and resource allocation. The process framework standardizes this approach, ensuring consistency across different contexts and enabling reliable comparisons and adjustments based on forecasted outcomes.
- **Insight into Variables and Best Practices Incorporation:** Predictive modelling identifies crucial factors affecting academic performance in AI, such as student engagement and the specifics of AI tool applications. The framework enhances this by ensuring that data collection and analysis follow best practices in data science, educational technology, and ethics, focusing on enhancing predictive model relevance and applicability.
- **Scalability and Iterative Improvement:** Direct data collection offers valuable insights but is not always scalable. A predictive model, underpinned by a process framework, can be broadly applied and continuously refined. This iterative improvement process ensures that models remain accurate and relevant as educational contexts and technologies evolve.
- Efficiency and Resource Optimization: Predictive models provide quicker assessments, allowing real-time educational strategy adjustments. The process framework underlines this efficiency by offering a clear roadmap for development, ensuring targeted and efficient resource allocation towards activities that significantly impact model quality and utility.

- **Customization and Stakeholder Engagement:** Understanding how students might respond to AI-based learning tools enables more personalized experiences. The process framework fosters stakeholder engagement, ensuring that predictive models reflect diverse needs and perspectives for more effective AI integration strategies.
- **Longitudinal Studies and Outcome Focus:** Predictive models simulate long-term AI adoption effects, which are crucial for sustainability and long-term benefits. The process framework ensures these efforts align with educational outcomes, focusing on initiatives significantly enhancing learning and teaching.
- **Cost-Effectiveness and Scalability:** Developing a predictive model is more cost-effective than continuous data collection and analysis. The framework emphasises this cost-effectiveness and facilitates model scalability and replicability across different educational settings, broadening AI's educational impact.
- **Transparency and Accountability:** A well-defined process framework increases the transparency of how predictive models are developed and used, helping to gain the educational community's trust and ensuring accountability in decision-making.

Incorporating a process framework for predicting the impact of AI adoption on academic performance thus not only enhances predictive modelling efforts but ensures that these initiatives are consistent, collaborative, transparent, and ultimately focused on improving educational outcomes. This cohesive approach leverages the strengths of both predictive modelling and structured frameworks to optimize the integration of AI into educational systems, ensuring that the adoption of AI tools is as effective and beneficial as possible.

This current research investigates the regional differences in the developed framework using West Africa (with Nigeria as a case study) and North America (with Canada as a case study). These regions' social, political, and economic structures vary significantly, making them ideal for comparative analysis. The project begins with a scoping review of existing literature, aiming to develop an extrapolative decision support system. A modified Machine Learning (ML) algorithm improves model accuracy. Specifically, Support Vector Machine (SVM) is utilised to analyze the complex relationship between AI adoption and academic performance. The SVM model is explored and potentially modified to enhance its accuracy depending on the characteristics of the datasets. Previous studies have demonstrated that different approaches to the same problem can yield varying outcomes (Nourani, Gökçekuş, and Umar, 2020). This research aims to minimize error variance and produce more reliable results than traditional models (e.g., Structural Equation Model or Statistical Method) used in the eLearning domain by employing a modified ML algorithm.

The study's findings help identify the factors influencing AI adoption and gender differences in AI application adoption in Open and Distance Learning (ODL) settings. This understanding is valuable for developers, higher education providers, policymakers, and the government in promoting gender inclusion and meeting students' needs through AI-based application platforms. To ensure the ethical integrity of the research, it underwent scrutiny by an Ethics committee and received approval from the National Open University's Faculty Research Ethics Committee (FREC). Adhering to the fundamental ethical principles of human subject protection, including respect for persons, beneficence, and justice, will be paramount throughout the research process.

Over the last few decades, the intersection of artificial intelligence (AI) and education has garnered considerable attention from researchers across disciplines. As Hwang et al. (2020) indicated, advances in computing and data processing techniques have expedited AI development, primarily intending to mimic intelligent human behaviour such as inference, analysis, and decision-making. The anticipation is to witness a surge of research focusing on how AI can be seamlessly integrated into classrooms and how AI expertise can be imparted to students across different educational levels. Chaudhry and Kazim (2021) offered a recent overview of AI in Education (AIEd) research, underlining its potential to reduce teachers' burden, personalise learning experiences, revolutionise assessments, and contribute to intelligent tutoring systems' progression. The study suggests that the central thesis of AIEd is to bolster education rather than merely promote AI. Groundbreaking AI from international researchers and businesses is valuable only if it aids students in their learning journeys. Thus, learning outcomes are the ultimate yardstick for evaluating AI's impact on education.

In this regard, Hwang et al. (2020) have underscored several research directions in AIEd, including scrutinizing AI-based learning systems' efficacy from diverse viewpoints. Four primary domains surfaced where AI applications in education were found: profiling and prediction, assessment and evaluation, adaptive systems and personalization, and intelligent tutoring systems. These applications predominantly reside within academic support services and institutional and administrative services. The vast majority of AI in education literature is situated within computer science and STEM fields, and empirical investigations mainly employ quantitative methodologies such as the structural equation modelling approach. This present work investigates AIEd's role in supporting education by studying its applications in Online Distance Learning (ODL) settings. This includes exploring the factors that stimulate its adoption, the impacts of these factors on students' academic performance, and the role of gender and regional differences in its adoption. The research employed quantitative methodologies, specifically Machine Learning Modelling, to examine these factors in ODL settings in West Africa and North America.

Popenici and Kerr (2017) studied AI systems' influence on learning and teaching, unearthing potential discord between learners and educators. Their work accentuates the necessity to comprehend AI systems' impact on learner-educator interactions in the online learning milieu. Roll and Wylie (2016) advocated for the increased involvement of AI systems in learner-educator communication and educational applications beyond the school context, suggesting that AI systems could significantly enhance online learner-educator interactions. Demir and Yurdugül's teacher readiness model encompasses eight critical components: acceptance, technology access, motivation, self-efficacy, perceived ease of use, perceived usefulness, perceived enjoyment, and social influence. These factors are considered fundamental for adopting online distance learning (Demir and Yurdugül, 2015).

The technology acceptance model (TAM) has evolved into a theoretical framework for using and accepting online technologies. Muhaimin et al. (2019) suggest that these models rely on a range of concepts, including attitude towards technology, perceived ease of use of the technology, and perceived usefulness of the technology. Muhaimin et al. (2019) conducted a study during the COVID -19 pandemic in Malaysia to evaluate the factors influencing the intent to use online distance learning technology. They discovered a significant impact of perceived ease of use, perceived usefulness, and attitude towards technology on the intent to use online distance learning technology.

The AI in Education (AIEd) community is increasingly scrutinizing the impact of AI systems on online education. Uunona and Goosen (2023) noted that AI and machine learning have substantial potential to transform educational institutions. An abundance of scholarly work exists concerning implementing AI in education, especially in the context of Online Distance Learning (ODL) (Picciano, 2017; Haenlein & Kaplan, 2019). The promise of AI delivering personalized and adaptive learning is a powerful catalyst for its uptake, accompanied by advantages like improved efficiency and heightened student engagement, as mentioned in various studies (Tiwari, 2023; Hashim et al., 2022).

The principal interest of this research is to investigate the effect of AI on learners' academic achievement. Numerous research studies support the hypothesis that AI's personalized learning and prompt feedback significantly bolster students' academic performance in ODL contexts (Zhu et al., 2018; Akyuz, 2020). Further, implementing intelligent tutoring systems has been associated with enhanced learning outcomes (Akyuz, 2020; Ali et al., 2023). Existing research offers encouraging results in forecasting student performance using a Support Vector Machine (SVM). This exploration uses machine learning techniques, specifically SVM, to predict student outcomes in online learning by considering past performance, engagement metrics, and behavioural patterns. SVM has proven effective in forecasting student results in ODL settings (Alqahtani, 2021). For instance, one study illustrated SVM's capacity to predict student engagement levels, which are crucial predictors of academic achievement. Another study examined the prediction of student academic achievement during online learning utilizing regression in SVM. Factors such as attendance, participation, and quiz scores were used to predict academic achievement, with results demonstrating SVM's high efficiency in this task (Samsudin et al., 2022).

Academic performance prediction is a crucial aspect of online education as it helps identify students at risk of failure, enables personalized learning pathways, and optimizes instructional design (Asif et al., 2017; Chen et al., 2020; Roll and Wylie, 2016). Various AI algorithms have been employed in previous studies to predict students' examination performance using classification and regression techniques (Tomašević et al., 2020). For instance, researchers have used multiple machine learning techniques, such as Naïve Bayes and k-nearest neighbours, to categorize students as "pass" or "fail" ((Jiao et al., 2022). Other studies have explored learning algorithms to classify student results into different categories, including "pass" or "fail," high, middle, and low levels, and multiple classes based on achieved grades (Sandra et al., 2021). Some research has focused on predicting student failure or developing early warning systems using genetic programming and data mining algorithms (Nagy & Molontay, 2023; Jiao et al., 2022).

Wang, Liu, and Tu (2021) employed a structural equation modelling (SEM) approach to investigate teachers' continued intention to teach with AI. They examined factors such as anxiety, self-efficacy, attitude towards artificial intelligence (AI), perceived ease of use (PEU), and perceived usefulness (PU). The study aimed to understand the interactions among these factors and their influence on teachers' intention to use AI in their teaching. The research involved 311 higher education professors, and the SEM analysis revealed that PU, PEU, self-efficacy, and attitude towards AI explained a significant portion of the variation in teachers' behavioural intention. Attitude towards AI had the most substantial impact, followed by self-efficacy. The study found a positive relationship between teachers' self-efficacy and the adoption of AI-based applications, which, in turn, influenced PEU, attitude towards AI, and PU.

Interestingly, a negative correlation was observed between teachers' self-efficacy and their attitudes towards using AI-based applications. This suggests that enhancing self-efficacy could reduce reluctance to adopt such applications in teaching. The study utilized the SEM approach, and its results were compared with machine learning modelling methods. Besides classification and regression, AI-enabled prediction models have been developed to forecast academic performance based on specific input variables characterizing student learning. These models can be categorized into similarity-based, model-based, and probabilistic approaches (Tomašević et al., 2020). However, there are gaps in the current development of prediction models concerning data identification and analytics. Many studies consider various student information data, such as demographics, without explicitly focusing on variables that reflect the specific learning process (Kurniawan et al., 2022). To address this issue, researchers should deliberately select student data aligned with learning theories and the principles of student-centred learning. Promisingly, emerging studies are exploring process-oriented online learning behaviour data to accurately predict academic performance, moving beyond traditional student information or performance data (Bernacki et al., 2020). This research project designs a collaborative learning mode in online courses that aligns with this trend. It deliberately selects student data from the collaborative process to make accurate academic performance predictions.

A review by Manhica, Santos, and Cravino (2022) provides an overview of AI applications in learning management systems (LMS) within higher education. The review found that Moodle is the most popular LMS for implementing AI solutions, and AI modelling has been extensively used to assess student performance. This review also emphasises exploring the moderating factors influencing AI adoption, such as gender and regional differences. Although a dearth of literature directly addresses gender differences in AI adoption, extant studies imply that gender-based biases may unintentionally find their way into AI systems, possibly influencing user interactions and academic results (Daraz et al., 2022). Concerning regional differences, variations in AI adoption rates are apparent, probably due to disparities in technology infrastructure and cultural perceptions of technology (Pillai & Sivathanu, 2020). The study discusses factors shaping the adoption of AI technology across different regions, like the availability of infrastructure, cultural attitudes towards technology, and economic impacts. These factors can differ geographically and affect the rates of AI technology adoption.

Overall, these related works shed light on the driving factors behind AI adoption in online distance learning environments and their impacts on students' academic performance. They suggest AI systems' potential to enrich learner-educator interaction in online learning. The SVM approach can predict students' academic performance, considering factors like acceptance, technology access, motivation, self-efficacy, perceived ease of use, usefulness, enjoyment, and social influence. Furthermore, gender and regional differences as moderating factors can be considered to comprehend better AI adoption's impact on students' academic performance.

2.5 Summary/Meta-Analysis of Reviewed Related Works

2.5.1 Summary

The intersection of artificial intelligence (AI) and education has been a significant area of study over recent years, with researchers focusing on integrating AI into classrooms and imparting AI knowledge to students at all educational levels. Computational advancements have propelled AI's development, aiming to emulate human intelligence, including inferential and analytical capabilities (Hwang et al., 2020). AI's role in education (AIEd) has been explored comprehensively, highlighting its potential to alleviate teaching burdens, personalise educational experiences, transform assessments, and further the growth of intelligent tutoring systems (Chaudhry and Kazim, 2021). The crux of AIEd research is on enhancing education, with the impact on learning outcomes serving as the primary metric to assess the effect of AI in education.

Several research directions in AIEd have been proposed, which include examining the efficiency of AI-based learning systems. The applications of AI in education are typically observed within four primary areas: profiling and prediction, assessment and evaluation, adaptive systems and personalization, and intelligent tutoring systems. These applications are most commonly applied within academic support and administrative services. Most AIEd literature is found within Computer Science and STEM fields, primarily employing quantitative research methods, such as the Structural Equation Modeling Approach (Hwang et al., 2020).

The impact of AI on teaching and learning has been studied, revealing potential conflicts between teachers and learners (Popenici and Kerr, 2017). Roll and Wylie (2016) advocated for increased AI involvement in learner-educator communication and educational contexts beyond the classroom, suggesting that AI could substantially enhance online learner-educator interactions.
The adoption of online distance learning is influenced by several factors, such as acceptance, access to technology, motivation, self-efficacy, perceived ease of use, perceived usefulness, enjoyment, and social influence, as described in Demir and Yurdugül's teacher readiness model (Demir and Yurdugül, 2015). Similarly, the technology acceptance model (TAM) has emerged as a theoretical framework for the acceptance and usage of online technologies, which incorporates concepts such as perceived ease of use, perceived usefulness, and attitudes towards technology (Muhaimin et al., 2019).

The impact of AI systems on online education has been a growing focus for the AIEd community. AI and machine learning have demonstrated substantial potential to revolutionize educational institutions, particularly in Online Distance Learning (ODL) (Uunona and Goosen, 2023).
Predicting student performance using a Support Vector Machine (SVM) has shown promising results

in existing research. This technique uses machine learning to predict student outcomes in online learning by considering past performance, engagement metrics, and behavioural patterns. One study demonstrated the effectiveness of SVM in predicting student engagement levels, which are crucial predictors of academic achievement (Alqahtani, 2021). Gender and regional differences are significant moderating factors in AI adoption. While there is limited research on gender differences in AI adoption, some studies suggest gender-based biases may unintentionally be integrated into AI systems, potentially influencing user interactions and academic outcomes. Regional differences in AI adoption rates are likely due to disparities in technology infrastructure and cultural attitudes towards technology (Daraz et al., 2022; Pillai & Sivathanu, 2020).

Upon analysis of the related works in the field of artificial intelligence (AI) in education, a few key themes and findings become apparent:

I. **AI Development and Integration**: As highlighted by Hwang et al. (2020), the advancements in computing and data processing techniques have expedited the development of AI, with the primary focus on mimicking intelligent human behaviour. AI integration into classrooms and curricula is anticipated to surge thanks to its potential for inference, analysis, and decision-making.

II. **AI's Role in Education**: Studies like the one conducted by Chaudhry and Kazim (2021) illustrate AIEd's potential in several areas, including reducing teachers' workload, personalizing learning experiences, revolutionizing assessments, and enhancing intelligent tutoring systems. Moreover, the effectiveness of AIEd is ultimately measured by its impact on learning outcomes, which bolsters education rather than merely promoting AI.

III. **AI Applications in Education**: According to Hwang et al. (2020), AIEd's primary domains include profiling and prediction, assessment and evaluation, adaptive systems and personalization, and intelligent tutoring systems. These applications primarily support academic services and administrative services. The methodologies in these domains predominantly employ quantitative research methods such as the Structural Equation Modeling approach.

IV. **Learner-Educator Interactions**: The works of Popenici and Kerr (2017) and Roll and Wylie (2016) emphasize the importance of understanding the impact of AI systems on the dynamics between learners and educators. They advocate for more AI involvement in enhancing online learner-educator interactions.

V. **Acceptance of Online Distance Learning**: Demir and Yurdugül's (2015) model and the technology acceptance model (TAM) proposed by Muhaimin et al. (2019) highlight critical components influencing the acceptance of online distance learning technology, including acceptance, access to technology, motivation, self-efficacy, perceived ease of use, and usefulness, enjoyment, and social influence.

VI. **AI's Impact on Online Education**: Uunona and Goosen (2023) and others discuss the transformative potential of AI and machine learning in educational institutions, specifically in Online Distance Learning (ODL).

VII. **Predicting Student Performance**: Using a Support Vector Machine (SVM) to predict student performance has shown promising results in the studies analyzed. The focus is on past performance, engagement metrics, and behavioural patterns (Alqahtani, 2021; Samsudin et al., 2022).

VIII. **Moderating Factors in AI Adoption**: The review identifies gender and regional differences as important moderating factors in AI adoption. Gender-based biases in AI systems, disparities in technology infrastructure, and cultural attitudes towards technology across regions are noteworthy (Daraz et al., 2022; Pillai & Sivathanu, 2020).

2.5.2 Meta-analysis

The included fifty-three articles are given in Table 2.1. The articles that addressed factors driving AI adoption, the impact of AI adoption on academic performance in ODL, the use of Support Vector Machine (SVM) for predicting academic performance, and the moderating factors of gender and regional differences were considered. The selection was based on the extent to which the articles significantly contributed to understanding these aspects and provided valuable insights and findings related to AI adoption and its impact on academic performance in ODL.

In this review, Machine Learning Methods were the most commonly used, accounting for 28.3% of the studies. This shows a significant interest in using machine learning techniques in the field and suggests that future research will continue to leverage these techniques to gain insights. Classical Statistical Methods were used in 22.6% of the studies. Although these methods might not be as cutting-edge as machine learning, they still play a crucial role in many research studies. Hybrid Methods were used in a very small proportion of the studies, specifically 3.8%. Non-empirical methods were used in 45.3% of the studies, making this the largest category. These methods include theoretical analyses, literature reviews, and other non-data-driven approaches. The distribution of the methodology used in the included studies is shown in Table 2.2. The chart that represents the methodology of the selected studies is shown in Figure 2.4. The chart illustrates the distribution of different research methods across the selected studies. The temporal distribution of articles included in this review (See Figure 2.5) reveals significant insights into the progression of research within the field.

A total of 53 articles spanning from 2015 to 2023 were analyzed. The number of articles published each year exhibited a general trend of increase over this period. A solitary article was published in 2015 and 2016. The year 2017 saw a modest increase with three articles. The figure dropped slightly to one in 2018, then increased to four in 2019. The year 2020 marked a substantial increase in publications, with six published articles. This upward trend continued into 2021 with a notable surge to 12 publications. The year 2022 saw the peak of this trend, with the highest number of articles - 16 - being published in a single year.

Table 2.1 The studies included in the final selection

S/N	Year of Publication	Articles	Methodology of the study
1	2015	Demir and Yurdugül, 2015	Non-Empirical Method
2	2016	Roll and Wylie, 2016	Non-Empirical Method
3	2017	Popenici and Kerr, 2017	Non-Empirical Method
4		Asif et al., 2017	Machine Learning Method
5		Picciano, 2017	Non-Empirical Method
6	2018	Zhu et al., 2018	Non-Empirical Method
7	2019	Gardner et al., 2019	Statistical Method
8		Mduma et al., 2019	Non-Empirical Method
9		Muhaimin et al., 2019	Statistical Method
10		Haenlein & Kaplan, 2019	Non-Empirical Method
11	2020	Nguyen et al., 2020	Non-Empirical Method
12		Tomasevic et al., 2020	Machine Learning Method
13		Bernacki et al., 2020	Machine Learning Method
14		Hwang et al., 2020	Non-Empirical Method
15		Chen et al., 2020	Non-Empirical Method
16		Akyuz, 2020	Statistical Method
17	2021	Horowitz and Kahn, 2021	Statistical Method
18		Khan et al., 2021	Machine Learning Method
19		Seo, Tang, Roll, Fels, & Yoon, 2021	Statistical Method
20		Youmei Wang, Liu, & Tu, 2021	Statistical Method
21		Alqahtani, 2021	Machine Learning Method
22		Wang, Liu, and Tu, 2021	Machine Learning Method
23		Chaudhry and Kazim, 2021	Non-Empirical Method
24		Ayouni et al., 2021	Machine Learning Method
25		Toplic, 2021	Non-Empirical Method

Table 2.1 The studies included in the final selection (Contd.)

S/N	Year of Publication	Articles	Methodology of the study
26		Sandra et al., 2021	Machine Learning Method
27	**2021**	Huang et al., 2021	Non-Empirical Method
28		Kuleto et al., 2021	Non-Empirical Method
29		Almaiah et al., 2022	Statistical Method
30		Kurup & Gupta, 2022	Statistical Method
31		Alam et al., 2022	Statistical Method
32		Bertl et al., 2022	Non-Empirical Method
33		Jiao et al., 2022	Machine Learning Method
34		Cruz-Jesus et al., 2020	Hybrid
35		Xiao et al., 2021	Machine Learning Method
36		Hashim et al., 2022	Non-Empirical Method
37	**2022**	Samsudin et al., 2022	Machine Learning Method
38		Manhica, Santos, and Cravino, 2022	Non-Empirical Method
39		Daraz et al., 2022	Non-Empirical Method
40		Pillai & Sivathanu, 2022	Hybrid
41		Kurniawan et al., 2022	Statistical Method
42		Liu & Huang, 2022	Statistical Method
43		Ogunsola-Bandele & Kennepohl, 2022	Statistical Method
44		Gao, 2022	Machine Learning Method
45	**2023**	Ouyang et al., 2023	Machine Learning Method
46		Holicza & Kiss, 2023	Machine Learning Method
47		Ali et al., 2023	Non-Empirical Method
48		Tiwari, 2023	Non-Empirical Method
49		Nagy and Molontay, 2023	Machine Learning Method
50		Uunona and Goosen, 2023	Non-Empirical Method
51		O'Dea & O'Dea, 2023	Non-Empirical Method
52		Tanjga, 2023	Non-Empirical Method
53		de la Torre-López, Ramírez, & Romero, 2023	Non-Empirical Method

Table 2.2 Methodology of the selected studies

S/N	Method of Research	Number of Articles	Percentage
1	Machine Learning Method	15	28.30%
2	Classical Statistical Method	12	22.64%
3	Hybrid Method	2	3.77%
4	Non-Empirical Method	24	45.28%

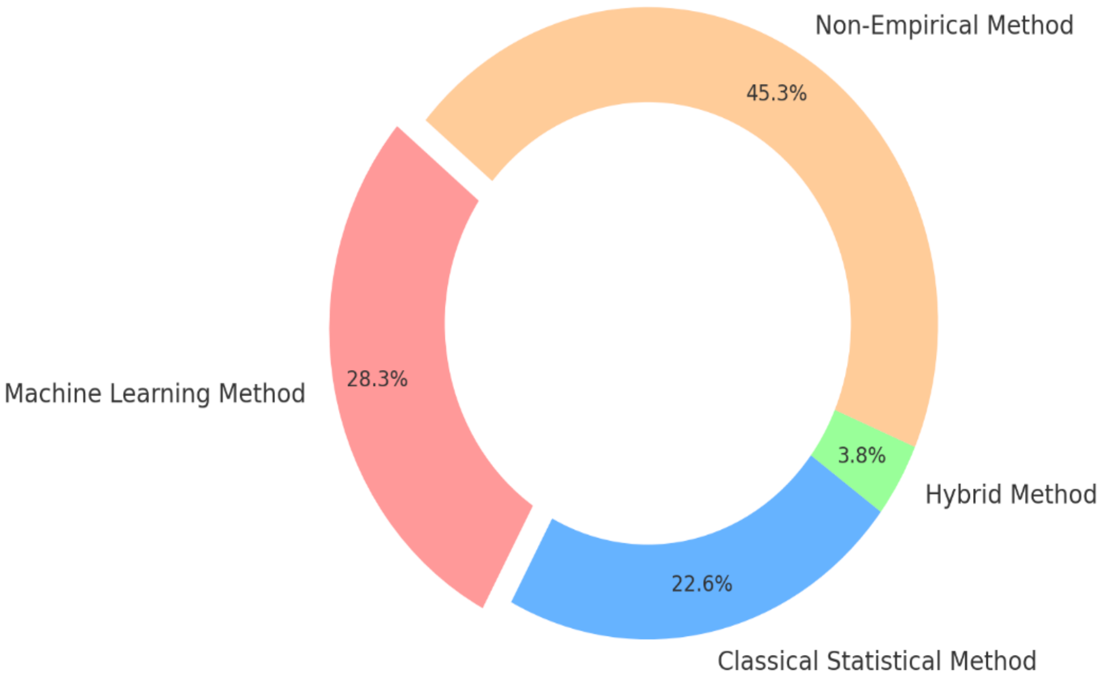


Figure 2.4 Percentage Distribution of the Method Used

However, in 2023, there was a slight decrease in the number of publications, with nine published articles. This dip could be attributed to the fact that the year was not yet over at the time of this review, or it could signal a new trend in the distribution of articles. This temporal distribution suggests a growing interest in the field, as reflected by the increasing number of articles published yearly. It also implies that the topics addressed by these articles are gaining traction in the research community, leading to a proliferation of studies and published works. This increasing trend in publication volume over the years points to the growing relevance and importance of this field and the need for continued research to keep pace with its rapid development. As such, the findings of this review are timely and pertinent to the current state of the field.

In this analysis, the journals mentioned in the dataset were examine based on their SCImago Journal Rank (SJR) and impact factor values. These metrics are widely used to assess the significance and influence of academic journals within their respective fields. Table 2.3 provides a list of articles along with the journals they were published in, the SCImago Journal Rank (SJR) for those journals and the impact factor of the journals. The high Impact Factors and SJRs of some of these journals indicate that the articles have been published in reputable journals and have a high potential for being cited in other works, which adds credibility to the articles. Here are some key insights from the provided data:
Journal Preference: The journal 'Computers & Education' seems to be a popular choice for publication, with multiple entries listed. This suggests the journal's relevance and importance in the field of study.

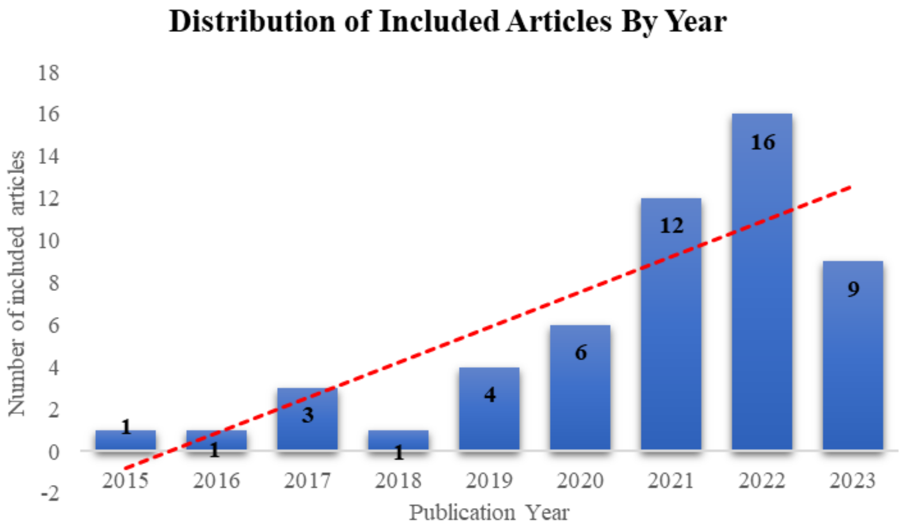


Figure 2.5 Distribution by year of the Articles included in the study

Journal Metrics: Generally, a higher SJR and Impact Factor are desirable as they suggest a more influential journal in the field. Notably, 'The Journal of Innovation & Knowledge' holds the highest SJR (2.649) and the highest Impact Factor (20.310) among the listed journals. This indicates the high recognition and influence of this journal. Figures 2.6-2.7 visually represent the top 10 journals by Impact Factor and SJR. 'Computers & Education' and 'Journal of Innovation & Knowledge' stand out in their respective categories, which supports the written findings.

Variation in Metrics: There is a wide variation in both SJR and Impact Factor across the different journals. This suggests a broad range of influence and reach for the listed journals.

Journals with Missing SJR and Impact Factor Information:

Some journals, including the International Journal of Progressive Education, International Learning Analytics & Knowledge Conference (LAK19), and Proceedings of the 53rd Hawaii International Conference on System Sciences, do not have an SJR or Impact Factor listed. This absence of data, marked as 'N/A', could stem from various reasons. For instance, these metrics might not be available for certain journals or conference proceedings. Alternatively, these could be relatively new or specialized journals for which such metrics have not yet been established. The lack of SJR and Impact Factor values makes it challenging to assess these journals' relative influence and reach within the academic community, at least through these particular metrics. However, it is essential to note that the evaluation of journals should not solely rest on these two metrics. The interpretation of SJR and Impact Factor values should be contextualized within the specific field or discipline of the journals.

In addition to these metrics, other factors like the journal's scope, the quality of the research it publishes, and its relevance to the research topic should also be considered when assessing the significance of a journal for a thesis or research study. This multi-faceted approach towards evaluation ensures a comprehensive understanding of the journal's standing and contribution to the field of study.

Table 2.3 Studies ranking and published journals

S/N	Articles	Journal Name	Scopus-SCImago Journal Rank (SJR)	Impact factor
1	Demir and Yurdugül, 2015	International Journal of Progressive Education	N/A	1.100
2	Roll and Wylie, 2016	Journal of Learning Analytics	1.369	4.760
3	Popenici and Kerr, 2017	Research and Practice in Technology Enhanced Learning.	0.654	3.440
4	Asif et al., 2017	Computers & Education	3.676	11.182
5	Picciano, 2017	Online Learning	1.417	5.030
6	Zhu et al., 2018	International Journal of Emerging Technologies in Learning	0.536	3.270
7	Gardner et al., 2019	International Learning Analytics & Knowledge Conference (LAK19)	N/A	N/A
8	Mduma et al., 2019	Data Science Journal	1.026	2.780
9	Muhaimin et al., 2019	Journal of Baltic Science Education	0.478	1.480
10	Haenlein & Kaplan, 2019	California Management Review	3.793	11.678
11	Nguyen et al., 2020	Proceedings of the 53rd Hawaii International Conference on System Sciences	N/A	N/A
12	Tomasevic et al., 2020	Computers & Education	3.682	15.58
13	Bernacki et al., 2020	Computers & Education	3.682	15.58
14	Hwang et al., 2020	Computers & Education	3.682	15.58
15	Chen et al., 2020	Computers & Education	3.682	15.58
16	Akyuz, 2020	Creative Education	N/A	0.500
17	Horowitz and Kahn, 2021	PLoS ONE	0.885	3.750
18	Khan et al., 2021	Smart Learning Environments	0.967	6.310
19	Seo, Tang, Roll, Fels, & Yoon, 2021	International Journal of Educational Technology in Higher Education,	2.051	10.42
20	Youmei Wang, Liu, & Tu, 2021	Educational Technology & Society	1.049	5.080
21	Alqahtani, 2021	Journal of Educational Computing Research	1.673	7.350
22	Wang, Liu, and Tu, 2021	Educational Technology & Society	1.049	5.080
23	Chaudhry and Kazim, 2021	AI And Ethics	N/A	N/A
24	Ayouni et al., 2021	PLoS ONE	0.885	3.750
25	Toplic, 2021	NetHope	N/A	N/A
26	Sandra et al., 2021	TEM Journal	0.231	1.210
27	Huang et al., 2021	Academic Journal of Interdisciplinary Studies	0.183	0.810
28	Kuleto et al., 2021	Sustainability	0.664	4.390
29	Almaiah et al., 2022	Electronics	0.148	0.530
30	Kurup & Gupta, 2022	A Journal of Management Research	0.567	3.460

Table 2.3 Studies ranking and published journals (Contd.)

S/N	Articles	Journal Name	Scopus-SCImago Journal Rank (SJR)	Impact factor
31	Alam et al., 2022	Education and Information Technologies.	1.249	7.65
32	Bertl et al., 2022	Frontiers in Psychiatry	1.222	4.52
33	Jiao et al., 2022	Artificial Intelligence Review	2.490	15.010
34	Cruz-Jesus et al., 2020	Heliyon	0.609	4.45
35	Xiao et al., 2021	Journal of Interconnection Networks	0.207	0.55
36	Hashim et al., 2022	International Journal of Academic Research in Progressive Education and Development	N/A	N/A
37	Samsudin et al., 2022	International Journal of Information and Education Technology	0.243	1.69
38	Manhica, Santos, and Cravino, 2022	2022 17th Iberian Conference on Information Systems and Technologies (CISTI).	0.146	0.493
39	Daraz et al., 2022	Computer and Information Science	0.924	6.053
40	Pillai & Sivathanu, 2022	Benchmarking	1.185	7.970
41	Kurniawan et al., 2022	Jurnal Pendidikan: Teori, Penelitian, Dan Pengembangan	N/A	N/A
42	Liu & Huang, 2022	Mathematical Problems in Engineering.	0.355	2.100
43	Ogunsola-Bandele & Kennepohl, 2022	In Tenth Pan-Commonwealth Forum on Open Learning.	N/A	N/A
44	Gao, 2022	Mathematical Problems in Engineering	0.355	2.100
45	Ouyang et al., 2023	International Journal of Educational Technology in Higher Education	2.051	10.420
46	Holicza & Kiss, 2023	Behav Sci (Basel)	0.597	2.980
47	Ali et al., 2023	Journal of Innovation & Knowledge	2.649	20.310
48	Tiwari, 2023	Indian Scientific Journal of Research in Engineering and Management	N/A	N/A
49	Nagy and Molontay, 2023	International Journal of Artificial Intelligence in Education.	1.110	4.980
50	Uunona and Goosen, 2023	In Advances in medical education, research, and ethics (AMERE)	N/A	N/A
51	O'Dea & O'Dea, 2023	Journal of University Teaching and Learning Practice	0.488	2.03
52	Tanjga, 2023	Qeios.	N/A	N/A
53	de la Torre-López, Ramírez, & Romero, 2023	Computing	0.824	4.331

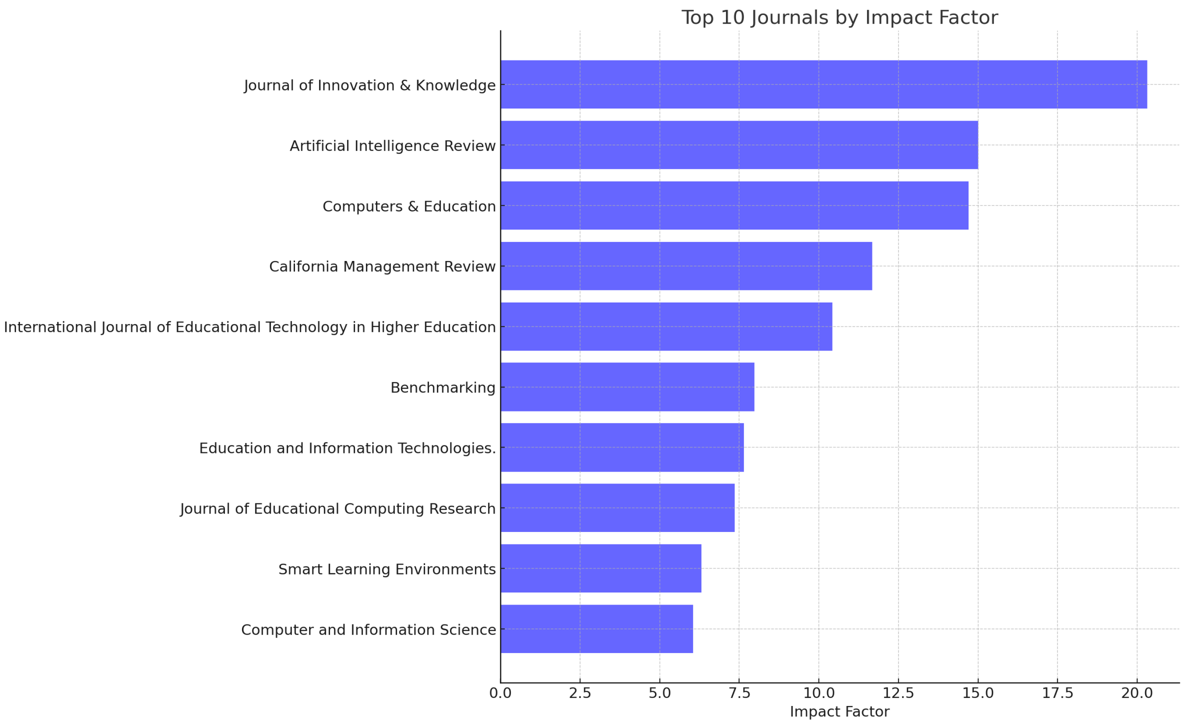


Figure 2.6 The Top 10 Journals by Impact Factor

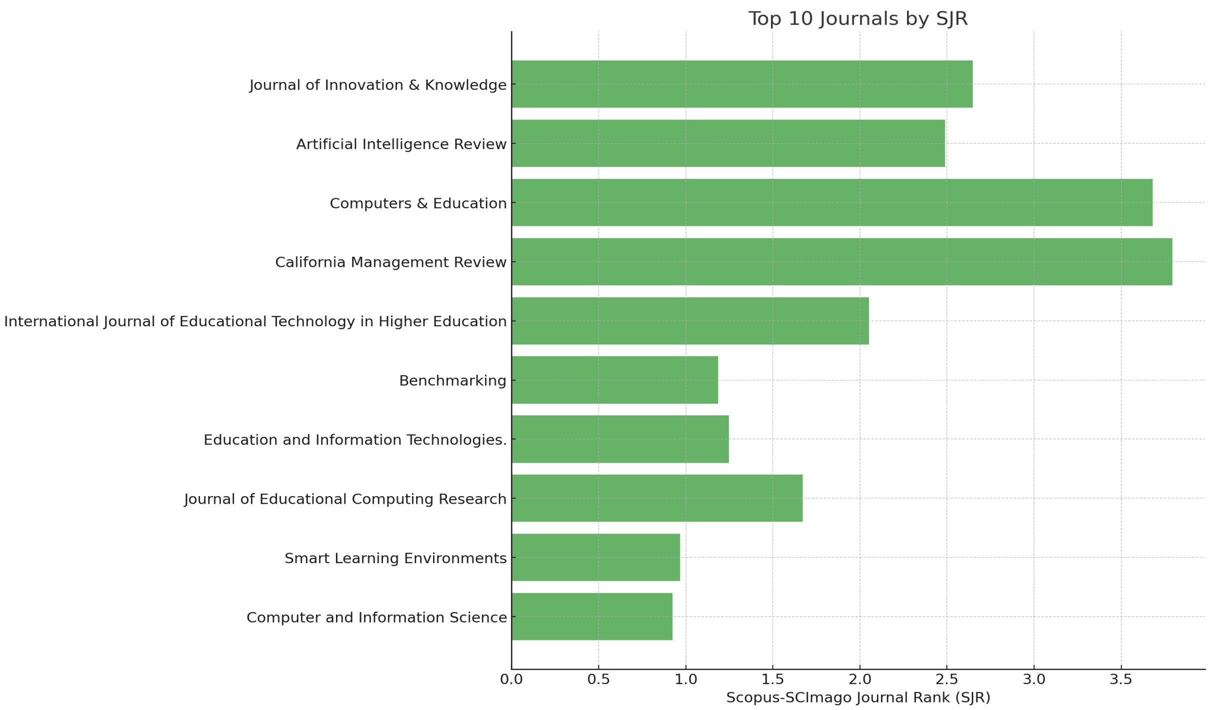


Figure 2.7 The Top 10 Journals by SJR

This comprehensive review of selected scholarly works underscores the potential and challenges of using artificial intelligence (AI) in education. AI can dramatically transform various dimensions of teaching and learning, acting as a potent force in the sector. However, alongside the many positive impacts, there are also potential pitfalls and negative impacts. This dichotomy highlights the crucial need for a robust process framework that can predict the impact of AI adoption on students' academic performance, particularly in open and distance learning (ODL) environments. The development and refinement of such a framework cannot be overstated, as it is instrumental in harnessing the positive potential of AI while mitigating its risks. Through this balanced and thoughtful approach, the potential of AI in education can be truly unlocked. Through the analysis of various research methods, the robust capabilities of machine learning methodologies, particularly Support Vector Machines (SVM), in predicting academic outcomes have been emphasized. This illuminates the strong and growing intersection between AI and education, with machine learning emerging as a powerful tool in education research.

The reviewed studies also shed light on the crucial drivers behind the adoption of AI in distance learning contexts. They underscore its far-reaching implications on student outcomes, indicating that AI can enhance the learning experience and potentially improve educational achievement.
Furthermore, the studies underscore the potential of AI to enrich the interaction between learners and educators in digital environments. This is particularly pertinent in online and remote learning, where AI could facilitate effective teaching and learning practices. The examination of intermediary factors such as gender and geographic disparities offers a deeper understanding of the complex dynamics at play in the integration of AI in education. This nuanced understanding aids in a more comprehensive appreciation of AI's potential positive and negative impacts on the educational sector. In essence, this review emphasizes the growing significance of AI in education, its potential impacts, and the importance of ongoing research in this rapidly evolving field.

CHAPTER THREE
METHODOLOGY

3.1 Preamble

The primary objective of this study is to explore the intricate relationship between the adoption of Artificial Intelligence (AI) and students' academic performance within the realm of Open and Distance Learning (ODL) environments. Specifically, the study aims to develop a resilient predictive framework utilizing the Support Vector Machine (SVM) algorithm. This section encompasses the proposed solution, technique, research model, framework, data source, mode of data collection, sampling technique, and modelling approach.

This study seeks to construct a detailed predictive framework using the Support Vector Machine (SVM) to understand the influence of AI adoption on students' academic performance within Open and Distance Learning (ODL) settings. Central to this effort is using AI adoption determinants as predictors for academic outcomes. The SVM, recognized for its proficiency in classification and prediction based on input data, is the backbone of this project. Leveraging the SVM's capabilities, the study endeavours to produce a model pinpointing the relationship between AI adoption and students' academic results.

The methodology for this research is layered and thorough. It commences with a rigorous literature review to identify the factors affecting AI adoption and their subsequent effects on academic success in ODL contexts. This literary exploration is enriched with specific data sourced directly from ODL institutions. In the subsequent design phase, visualization tools like Visio and draw.io are utilized to craft schematic diagrams, and the Unified Modeling Language (UML) shapes the architecture of the process framework and overall research model. Data analysis is primarily executed through Python, especially within platforms such as Anaconda Navigator and Jupyter Notebook, focusing on the SVM algorithm and using libraries like Pandas, Numpy, Sklearn, matplotlib, and Imblearn. To assess the integrity and effectiveness of the developed machine learning models, they undergo evaluation using metrics like Mean Squared Error, Mean Absolute Error, and Accuracy.

3.2 Problem formulation

This study aims to develop a process framework to predict how AI adoption influences students' academic performance in ODL. AI can potentially improve learning outcomes and tailor education to individual needs, but it may also pose challenges such as loss of diversity, increased stress, and reduced autonomy. Moreover, the impact of AI adoption may vary depending on students' gender and geographical region. This study focuses on Nigeria and Canada as two contrasting cases of ODL contexts. The study used SVM modelling as a predictive technique to create the framework. It collected and analyzed data on AI adoption and academic performance in ODL and examined how gender and geographical region moderate this relationship. The study offers valuable insights into the benefits and drawbacks of AI integration in ODL and suggests evidence-based strategies for optimizing its use. The principal goal is to enhance the quality and relevance of ODL for students across different settings.

3.3 Proposed solution, technique, model or process framework

The following section provides an in-depth outline of the proposed solution, including the technique, research model, framework, data sources, data collection methods, sampling technique, and modelling approach.

3.3.1 Machine Learning Approach

The SVM machine learning algorithm was utilized to construct the envisioned predictive model. As shown in Figure 3.1, the machine learning project workflow was adhered to in its customary stages. The machine learning life cycle was stringently observed in the present study. Through the implementation of the Python programming language, the data analysis process was executed, and the requisite algorithm was authored to create the predictive model.

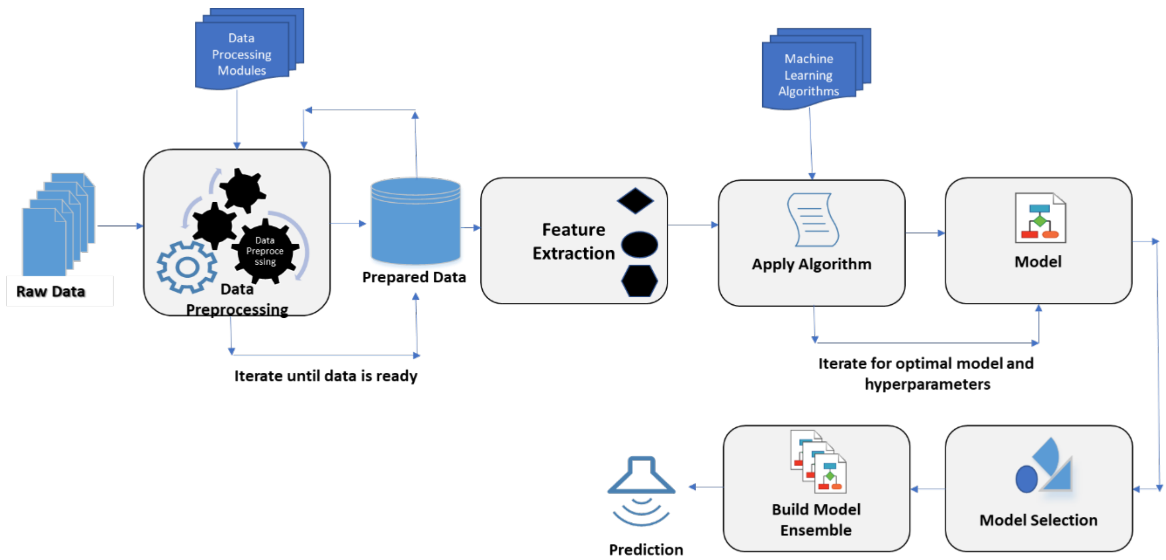


Figure 3.1 Typical Machine Learning Project Workflow

3.3.2 Proposed Process Framework

The research work utilizes a comprehensive process framework, which is detailed below. This framework is a systematic and structured approach to guide the investigation and analysis of the research objectives. The study aims to ensure coherence and effectiveness in its methodology and outcomes by following this framework. The adopted process framework encompasses several key steps that are executed sequentially to facilitate a thorough investigation.

I. **Identification of Key Factors:** This step involves identifying and selecting the key factors that influence the impact of AI adoption on students' academic performance in ODL. Relevant literature and empirical studies are reviewed to determine the critical factors significantly affecting the learning outcomes in AI-integrated ODL environments.

II. **Data Collection and Preprocessing:** In this phase, the process framework focuses on collecting relevant data related to the identified key factors. Data sources, such as student performance records, demographic information, AI usage data, and other relevant indicators, were considered. Preprocessing techniques were applied to ensure data quality and prepare the dataset for analysis.

III. **Feature Engineering and Selection:** This step involves transforming the collected data into meaningful features that can be utilized in the prediction process. Feature engineering techniques, such as data normalization, dimensionality reduction, and feature extraction, create a representative set of features for SVM modelling.

IV. **SVM Modeling and Prediction:** SVM was employed as the predictive modelling algorithm using the processed and engineered features. The SVM model was trained on historical data, leveraging its ability to analyze patterns and make predictions based on the identified key factors. The model's performance was assessed using appropriate evaluation metrics.

V. **Interpretation and Validation:** The final step of the process framework involves interpreting the results of the SVM model and validating the predictions against the actual students' academic performance in ODL. This step aims to assess the accuracy and reliability of the predictive model and gain insights into the impact of AI adoption on academic performance.

This process-driven framework (Refer to Figure 3.2) offers a systematic and organized approach to forecasting the implications of AI integration on students' academic achievements in ODL utilizing SVM. By amalgamating the theoretical underpinnings of AI, ODL, and SVM, this framework enhances the comprehension of the intricate relationships among AI integration, pivotal factors, and academic results. The framework serves as a directive for forthcoming empirical investigations and practical applications, empowering educational institutions to optimize the use of AI in ODL to elevate students' academic achievements and learning experiences. In conclusion, the methodological framework employed for this scholarly endeavour encompasses an all-encompassing approach that entails a literature review, formulation of research inquiries, data acquisition, meticulous analysis, predictive modelling, and interpretation of results. By adhering to this framework, the research aspires to ensure methodological consistency and yield valuable insights into the correlation between AI integration and students' academic performance in ODL settings.

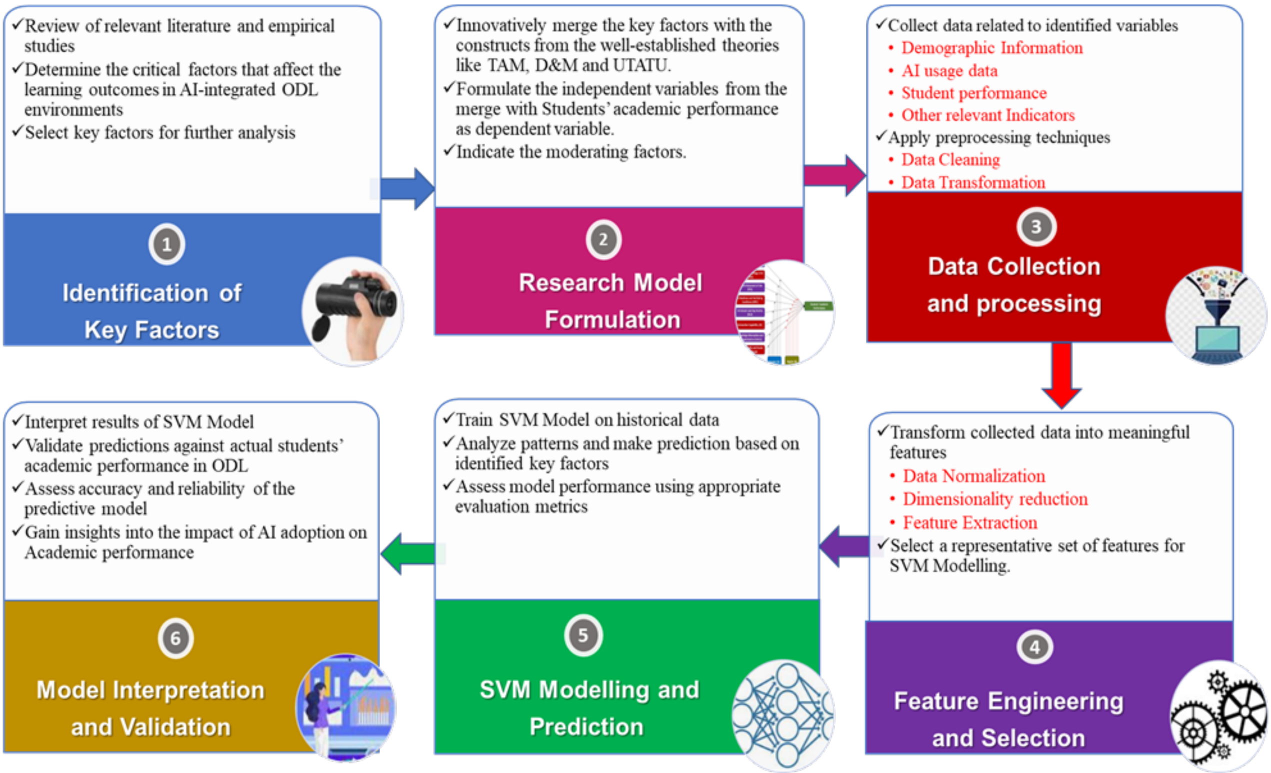


Figure 3.2 The Process Framework for Predicting the Impact of AI Adoption on Students' Academic Performance in ODL

In this diagram, each step is represented by a rectangular box, and the arrows indicate the workflow's flow. The diagram identifies key factors, followed by data collection and preprocessing. The processed data then goes through feature engineering and selection to create meaningful features for SVM modelling. The SVM model is trained on the data, and predictions are made based on the identified key factors. Finally, the results are interpreted and validated against actual academic performance data to assess the accuracy and gain insights. As described in Figure 3.2, the process Framework is independent of any predictive algorithm. The fundamental objective is to design a Process Framework that remains neutral with respect to particular machine learning algorithms. This impartiality is essential due to the ever-evolving nature of the educational environment, and associating our framework with a specific algorithm may lead to its obsolescence or diminished efficacy over time. By creating a model that is independent of any algorithm, flexibility, adaptability, and sustainability are guaranteed in its utilization.

A trio of models was intricately crafted and thoroughly compared for this doctoral study. Starting with a foundational process framework, as illustrated in Figure 3.2, the methodology evolved to integrate detailed procedural steps for each selected algorithm. This expanded and enriched layered architecture, which now includes these detailed steps, is presented in Figure 3.3. Each model, precisely crafted and aligned with research objectives, underwent a thorough comparative performance evaluation as part of the layered architecture's fifth step. This critical analysis aims to discern each model's effectiveness and accuracy, identifying its strengths and areas for improvement. This organized approach ensures the creation of robust and reliable models, aiming for academic excellence and practical applicability in understanding the research phenomena. Through strategic development and evaluation, the research aspires to unveil models that embody integrity and comprehensive analytical insights.

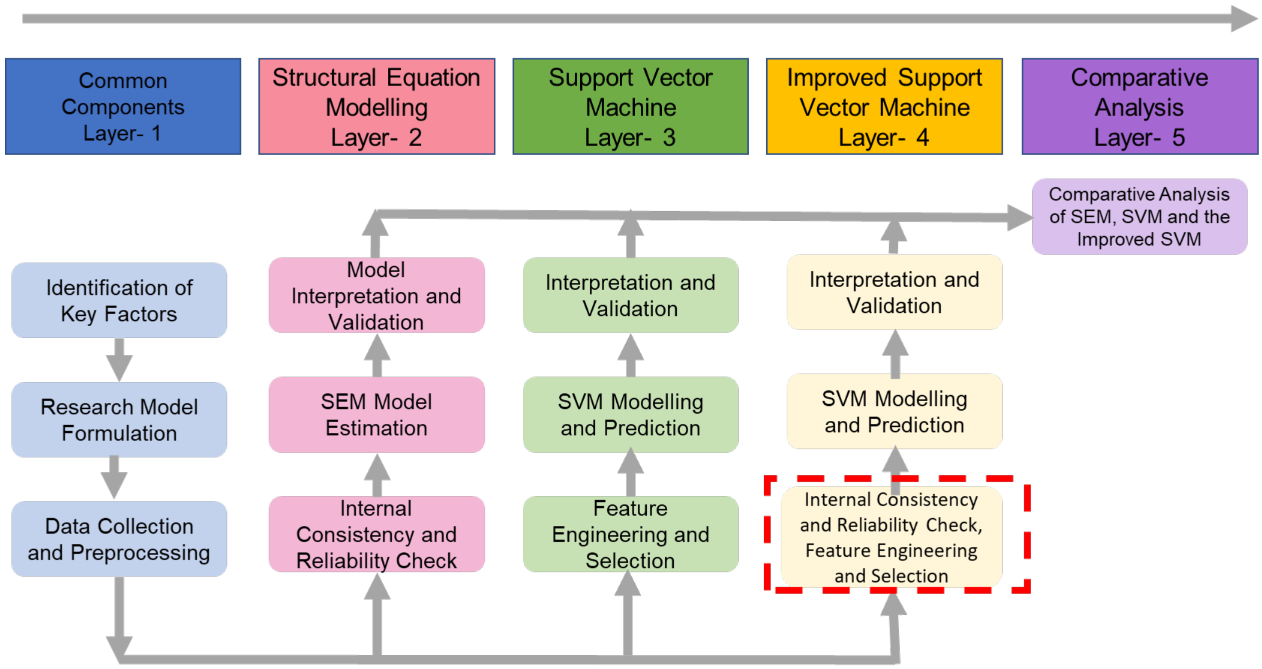


Figure 3.3 A Layered Architecture for Predicting AI Adoption on Students' Academic Performance in ODL using SEM, SVM and the improved SVM.

Figure 3.3 is the layered architecture that illustrates the distinct procedural stages of the three selected algorithms. This architecture is comprised of five layers, with the first layer encompassing three components. The second layer consists of three components. The third layer also includes three components. The fourth layer comprises three components. The fifth layer is represented by a singular component (M). Each layer has components described as follows:

Layer 1: Structural Equation Modelling (SEM) - Layer 1.

- **Identification of Key Factors:** This is the initial phase where crucial factors influencing AI adoption are identified through literature review and empirical studies.

- **Research Model Formulation:** Based on identified key factors, a research model is formulated to explore the relationships and impacts on academic performance.
- **Data Collection and Preprocessing:** This stage involves gathering data relevant to the research model and preprocessing it for analysis.

Layer 2: Structural Equation Modelling (SEM) - Layer 2

- **Internal Consistency and Reliability Check:** At this stage, the reliability of the model's constructs is assessed through methods like Cronbach's alpha.
- **SEM Model Estimation:** The SEM estimates the relationships between the identified factors and the outcomes.
- **Model Interpretation and Validation:** The final stage in SEM is where the model's findings are interpreted and validated against empirical data.

Layer 3: Support Vector Machine (SVM) - Layer 3

- **Feature Engineering and Selection:** This step focuses on selecting and engineering the most relevant features from the data for the SVM model.
- **SVM Modelling and Prediction:** An SVM model is developed to predict the outcomes based on the engineered features.
- **Interpretation and Validation:** The predictions of the SVM model are interpreted, and its performance is validated.

Layer 4: Improved Support Vector Machine (SVM) - Layer 4

- **Internal Consistency and Reliability Check, Feature Engineering and Selection:** Similar to Layer 3, but focusing on an improved SVM model that enhances the model’s stability and reliability by reducing the multicollinearity among the independent variables. The reduced Variance Inflation Factor (VIF) after applying the Internal Consistency and Reliability Check confirms the reduction in multicollinearity.
- **SVM Modelling and Prediction:** This improved SVM model is employed for more accurate predictions.
- **Interpretation and Validation:** The results of the improved SVM model are interpreted and validated for their accuracy and reliability.

Layer 5: Comparative Analysis Layer - 5

- **Comparative Analysis of SEM, SVM, and the Improved SVM:** This final layer involves a comparative analysis of the results from SEM, standard SVM, and improved SVM models to determine the most effective approach for predicting the impact of AI adoption on ODL academic outcomes.

The arrows suggest the flow direction in the layered architecture for refinement and validation across the models. This ensures that each approach is rigorously evaluated and that the best model is selected based on empirical evidence.

Based on the expanded framework in Figure 3.3, the overview of the research methodology is described in Figure 3.4 which presents an overview of the research methodology in a step-by-step, algorithmic fashion, illustrating the logical flow from one stage to the next. The process starts with defining the research objectives, which involve designing a process framework to understand AI adoption in Open and Distance Learning (ODL), developing a research model, and creating machine learning models to predict the impact of AI on student academic performance.

Following the definition of objectives, the next step is to identify key factors influencing AI adoption through a comprehensive literature review. These factors are then translated into model variables, and relationships between them are established to formulate the research model. Once the model is developed, data is collected via surveys and academic databases, and it undergoes preprocessing, including cleaning and normalization, to prepare it for analysis.

Internal consistency and reliability checks, such as Cronbach's alpha, are applied to ensure the data's reliability. After that, feature engineering is conducted to transform the data into relevant features suitable for machine learning models, and dimensionality reduction techniques are employed if necessary. The predictive models are then developed, including Structural Equation Modeling (SEM) and Support Vector Machines (SVM), with improvements made to the SVM model to enhance predictive capabilities.

Once the models are developed, they are interpreted and validated, and the predicted outcomes are compared with actual data. A comparative analysis is performed between the SEM, SVM, and improved SVM models to determine the most effective approach. The evaluation is conducted using performance metrics such as Absolute Mean Error and Mean Squared Error to assess model accuracy and efficiency in ODL contexts.

Finally, the findings are documented, offering insights into the impact of AI adoption on academic performance within ODL systems. The validated predictive framework is then presented as a valuable tool for educational institutions to assess and optimize AI's role in enhancing learning outcomes. This clear progression of steps emphasizes the systematic approach taken in the study to ensure rigor and accuracy in the analysis.

The methodology was designed to be iterative, allowing for refinements based on findings and validation results at each stage. This structured approach depicted in Figure 3.4 ensures a robust and comprehensive examination of AI's role in enhancing academic performance in ODL settings.

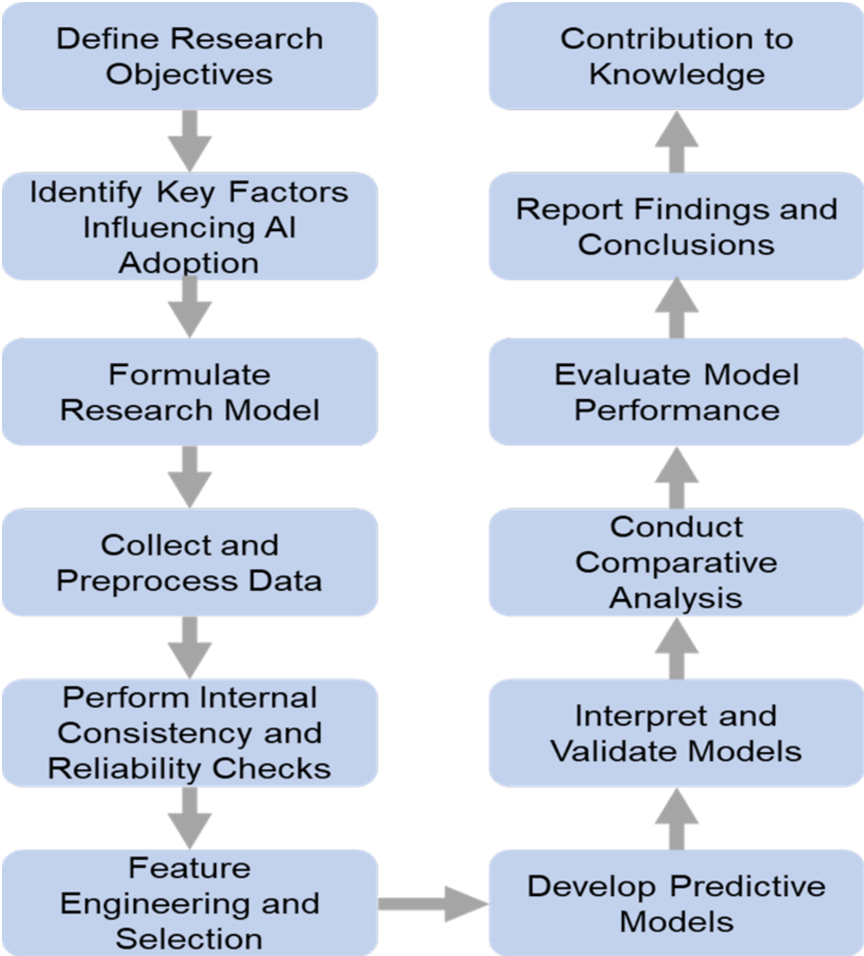


Figure 3.4 A flowchart showing the overview of the research methodology.

3.3.3 Implementation of Support Vector Machine Algorithm

Comprehending the mathematical intricacies that underlie the Support Vector Machines algorithm can unquestionably aid in understanding the implementation of the model. This understanding can provide valuable insights into selecting the most suitable model for a given problem and determining optimal values for hyper-parameters. As posited by Zhu (2021), the formulation of SVM is presented through a series of mathematical expressions delineated from Equations (1) through (13). These equations lay the foundation for constructing a hyperplane—a concept illustrated through Figures 3.5 through 3.7—effectively separating two classes in a feature space. This separation is critical for classification tasks, where the hyperplane's orientation and position, defined by vectors and margins, are optimized for the best division of classes. The mathematical particulars of Support Vector Machines are expounded below:

Consider that there are n training points, i has p features (i.e., x_i has p dimensions), and y_i is either

-1 or 1. Consider two classes of linearly separable observations. The implication is that a hyperplane can be drawn through the feature space, with all instances of one class on one side and all instances of the other class on the opposite side. (A *p-1* dimensional subspace is a hyperplane in *p* dimensions. A hyperplane is just a line in the following two-dimensional example.) A hyperplane is what is specified as:

(1)

where $\tilde{b}$ is a real number and $\tilde{w}$ is a *p*-vector. For ease, it is assumed that $\tilde{w} = 1$, so the distance from point x to the hyperplane is given by the formula $x *\tilde{w} +\tilde{b}$.

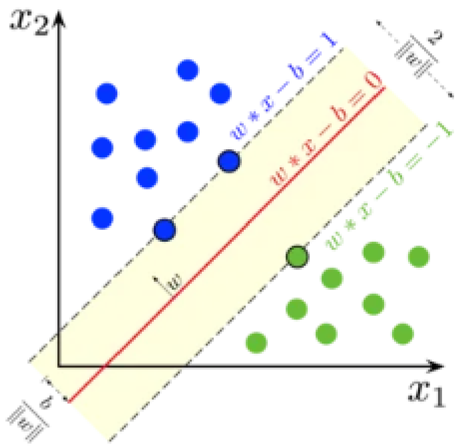


Figure 3.5 Key Concepts of SVM (Source: Zhu (2021))

Thus, the condition that the hyperplane divides the classes can be met by labelling the classes with $y = +1/-1$:

$$y_i\left(x_i \tilde{.} w + \tilde{b}\right) \geq 0 \qquad (2)$$

The Maximal Margin Classifier selects the plane that yields the largest margin M between the two classes and determines the best hyperplane.

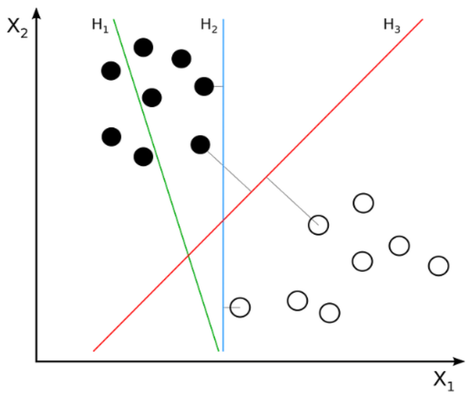


Figure 3.6 How to choose the best hyperplane (Source: Zhu (2021))

H_1 does not distinguish between the two classes in the previous graph; for H_2 and H_3, H_3 is chosen because H_3 has a larger margin. Given the constraints, mathematically, $\tilde{b}$ and $\tilde{w}$ are selected to maximize M:

$$y_i\left(x_i \tilde{.} w + \tilde{} b\right) \geq M \tag{3}$$

Defining w = $\tilde{w}$ / M and b = $\tilde{b}$ / M, this can be rewritten as:

$$y_i\left(x_i . w + b\right) \geq 1 \tag{4}$$

and

$$\|\tilde{w}\| = 1, \|\tilde{w}\| = \frac{1}{M} \tag{5}$$

Support vectors present a significant challenge in classification since they are the data points closest to the separating hyperplane. Their elimination would change the positioning of the dividing hyperplane, which is exclusively influenced by the support vectors through a weight-generating optimization algorithm. The optimization algorithm for generating the weights operates so that only the support vectors are accountable for determining both the weights and the boundary. Mathematically, support vectors can be defined as those points which are in closest proximity to the decision boundary and are defined as:

$$x_i * w + b = -1 \quad \textit{for negative class} \tag{6}$$

$$x_i * w + b = 1 \quad \textit{for positive class} \tag{7}$$

The hard-margin support vector machine (SVM) is a rigid method that imposes strict constraints on the support vectors that cross the hyperplane. It is designed to disallow any support vectors from being incorrectly classified. The optimization problem faced by the hard-margin SVM aims to maximise the hyperplane's margin.

$$\begin{gathered} \min_{\boldsymbol{w}, b} \frac{1}{2}\|\boldsymbol{w}\|^2 \\ \text{subject to } y_i(\boldsymbol{x_i} \cdot \boldsymbol{w} + b) \geq 1 \\ \text{for } i = 1, \ldots, n \end{gathered} \tag{8}$$

Soft-margin support vector machines (SVMs) are commonly used when dealing with non-linearly separable classes. The reason for such difficulty may be attributed to the absence of a clear class boundary or the presence of a non-linear boundary. To address this issue, SVMs employ slack variables, which permit a few points to cross or deviate from the margin. This can be observed in the accompanying graph. Hyper-parameter C controls the extent to which the slack variables are allowed to influence the SVM's decision boundary.

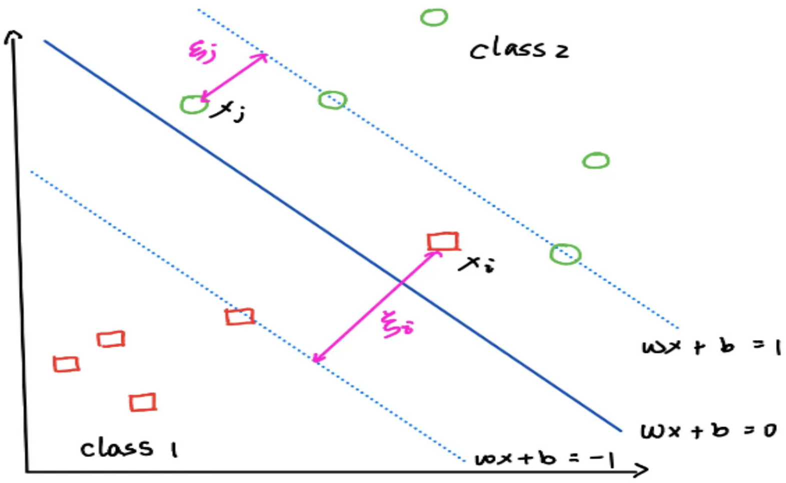


Figure 3.7 Soft-margin SVM and the hyper-parameter C (Source: Zhu (2021))

The soft-margin support vector machine aims to optimize the objective function by minimizing slacks and maximizi

$$\min_{\boldsymbol{w},b} \frac{1}{2}\|\boldsymbol{w}\|^2 + C\frac{1}{n}\sum_i \xi_i \tag{9}$$

$$\text{subject to} \begin{cases} y_i(\boldsymbol{x}\cdot\boldsymbol{w}+b) \geq (1-\xi_i) & \text{for } i=1,\ldots,n \\ \xi_i \geq 0 & \text{for } i=1,\ldots,n \end{cases}$$

The primal problem in optimization involves a constant C that represents the "cost" of slack. A smaller value of C is preferable when allowing more points into the margin is efficient, as it achieves a more significant margin. By increasing the number of support vectors, SVM reduces its variance, making the model more generalized. Therefore, decreasing C increases the number of support vectors and reduces overfitting. With Lagrange multipliers:

$$\alpha_i \geq 0 \text{ and } \mu_i \geq 0 \tag{10}$$

two constraints

The problem of constrained optimization can be rephrased as a primal Lagrangian function:

$$\min_{\boldsymbol{w},b,\xi} \max_{\alpha,\mu} \left[\frac{1}{2}\|\boldsymbol{w}\|^2 + C\frac{1}{n}\sum_i \xi_i - \sum_i \alpha_i\left[y_i(\boldsymbol{x}_i\cdot\boldsymbol{w}+b)-(1-\xi_i)\right] - \sum_i \mu_i\xi_i\right] \tag{11}$$

The dual Lagrangian formulation involves maximizing over the multipliers based on previously obtained relations for w and b rather than minimizing over w and b, subject to constraints.

$$\max_{\alpha} \left[\sum_i \alpha_i - \frac{1}{2} \sum_{i,i'} \alpha_i \alpha_{i'} y_i y_{i'} \boldsymbol{x_i} \cdot \boldsymbol{x_{i'}} \right] \tag{12}$$

$$\text{subject to } \begin{cases} 0 = \sum_i \alpha_i y_i \\ 0 \leq \alpha_i \leq C \quad \text{for } i = 1, \ldots, n \end{cases}$$

The task of optimizing a quadratic programming problem can be effectively tackled through the utilization of the Sequential Minimization Optimization methodology, and once optimized, the coefficients can be easily determined:

$$\boldsymbol{w} = \sum_i \alpha_i y_i \boldsymbol{x_i} \tag{13}$$

Walking through the mathematical underpinnings of Support Vector Machines is crucial in comprehending its implementation, as it guides the selection of the appropriate model for specific inquiries in this study and the determination of the optimal values for hyper-parameters.

In the context of Support Vector Machines (SVM) with a linear kernel, interpreting the impact of each predictor on the target variable can be more straightforward compared to non-linear kernels. When the predictors (features) are standardized before fitting the SVM model, each variable has been scaled to have a mean of zero and a standard deviation of one. This standardization allows for a more direct comparison of the coefficients' magnitudes in terms of their relative importance or impact on the target variable. However, it is important to note that SVMs do not provide coefficients like linear regression, but the weights (coefficients) in a linear SVM can still offer insights.

Here is how to interpret the impact of each predictor in a linear kernel SVM:

Understanding the Weights of a Linear SVM

For a linear SVM, the decision function is given by Equation (14) as:

$$f(x) = w^T x + b \tag{14}$$

- $\boldsymbol{w}$ is the weight vector, where each weight corresponds to a feature (predictor).
- $\boldsymbol{x}$ is the feature vector.
- $\boldsymbol{b}$ is the bias term.

The weight vector $\boldsymbol{w}$ holds the key to understanding the impact of each predictor on the target variable. Each weight in $\boldsymbol{w}$ corresponds to a feature, and its magnitude indicates the importance of that feature in determining the margin between the classes.

Interpreting the Weights:

I. Magnitude: The magnitude of each weight (ignoring the sign) indicates the relative importance of that feature in classifying the target variable. Larger magnitudes mean that the feature has a more significant impact on the decision boundary. Since the variables were standardized, these magnitudes can be directly compared to assess the more important features.

II. Sign: The sign of each weight indicates the direction of its impact. A positive weight suggests that higher values of that feature push the prediction towards one class, while a negative weight suggests that higher values push the prediction towards the other.

The steps to Interpret the Model are as follows:

I. Extract Weights: After fitting the linear SVM model, extract the weight vector w. This is typically accessible directly from the model object in most machine learning libraries like scikit-learn (e.g., ***model. coef_***).

II. Examine the Weights: Look at the magnitude and sign of each weight to understand each predictor's relative importance and direction of influence.

III. Report: For reporting, features and their corresponding weights can be listed, highlighting which features are most influential in the model and in which direction they influence the target variable.

3.3.4 Test for Multicollinearity

The Variance Inflation Factor (VIF) serves as a statistical instrument employed to identify multicollinearity among predictors within a regression framework. VIF assesses the extent to which the variance of an estimated regression coefficient is augmented as a result of multicollinearity. It quantifies the escalation in the variances of the regression parameter estimations attributable to collinear relationships among the predictors. A commonly accepted guideline posits that a VIF value surpassing 10 signifies substantial multicollinearity (Kim, 2019). The computation of VIF is delineated in Equation (15) for each predictor variable as follows:

$$VIF_i = \frac{1}{1 - R_i^2} \quad (15)$$

Where R_i^2 is the coefficient of determination derived from the regression of predictor i on all the other predictors. An elevated VIF suggests that the predictor exhibits a strong correlation with other predictors, thereby complicating the evaluation of the distinct contribution of each predictor to the variation observed in the response variable (Salmerón, García, & García, 2020).

In this study, reducing multicollinearity among the independent variables prior to applying the machine learning algorithms proved to be highly beneficial. By ensuring that the predictors were not highly correlated, the interpretability of the model was successfully improved, making it easier to understand the individual impact of each variable on the dependent variable. This reduction in multicollinearity also enhanced the stability of the model, preventing the coefficients from becoming overly sensitive to small changes in the data, thereby increasing the reliability of our results. Additionally, minimizing multicollinearity contributed to more accurate predictions by allowing the model to discern the true relationships between predictors and outcomes. It also helped in reducing the risk of overfitting, ensuring that the model did not rely on redundant information and thus performed better on new, unseen data. Furthermore, addressing multicollinearity streamlined the feature selection process, simplifying the identification of the most relevant predictors for the model. Overall, these efforts significantly improved the robustness and effectiveness of the predictive models developed in this research.

3.3.5 Study Area and Target Population

The study focuses on Open and Distance Learning (ODL) environments in two distinct geographical regions: Nigeria and Canada. These regions were chosen to represent different educational contexts and cultural backgrounds. The focus demographic encompasses students currently registered within ODL curricula in both nations., encompassing diverse age groups, academic disciplines, and educational levels.

3.3.6 Source of Data

The primary data source for this study is collected from the respective ODL institutions in Nigeria and Canada. Institutional collaboration and partnerships are established to gain access to the necessary data. Ethical considerations and institutional protocols are followed to ensure the confidentiality and privacy of the participants' information. The study employed a purposive sampling technique to select participants from ODL institutions. The sample included diverse students from various disciplines and educational levels. The goal is to comprehensively understand the impact of AI adoption on academic performance in different contexts. A large and diverse dataset was acquired by leveraging the power of quantitative survey methodology, enabling comprehensive analysis and reliable results.

3.3.7 Methods of data collection

Data were collected through surveys. The surveys were designed to gather relevant information about students' demographics, AI adoption in ODL, academic performance indicators, and the perceived impact of AI on their learning outcomes. The educational records provide objective measures of academic performance, such as grades, completion rates, and assessment scores. The survey questionnaires were distributed online using established data collection and management platforms.

The Cumulative Grade Point Average was obtained from the respective students, following the necessary data protection protocols and permissions.

3.3.8 Sample Size Determination

This section focuses on the rationale behind the determination of the sample size. The sample size is a critical aspect of research design that significantly impacts the reliability and validity of the study's findings. An adequately sized sample ensures that the study results are generalizable to the broader population while also providing sufficient power to detect meaningful effects or differences when they exist.

The importance of selecting an appropriate sample size cannot be overstated. A sample size that is too small may lead to a lack of statistical power, increasing the risk of Type II errors (failing to detect an existing effect). Conversely, a sample size that is too large may result in wasted resources and potentially increase the risk of Type I errors (detecting an effect that does not exist due to random chance). Thus, determining the optimal sample size is crucial for balancing these risks while ensuring the efficient use of resources (Shen et al., 2014).

This study's sample size determination was guided by several critical factors, including the study design, the expected effect size, the desired power level, and the significance level (alpha). The effect size refers to the magnitude of the difference or relationship the study aims to detect, which could be based on previous studies or theoretical considerations. The power of the study, typically set at 80% or higher, indicates the probability of correctly rejecting the null hypothesis when it is false. The significance level, often set at 0.05, defines the threshold for determining statistical significance (Albers & Lakens, 2018).

The formula for estimating sample size in quantitative studies was employed, taking into account the aforementioned factors to calculate the sample size. For instance, in comparing two means, the sample size for each group can be calculated using the formula as depicted in Equation (16):

$$n = \left(\frac{Z_{\frac{\alpha}{2}} + Z_{\beta}}{\delta} \right)^2 \sigma 2 \qquad (16)$$

Where n is the sample size per group, $Z_{\alpha/2}$ is the critical value of the normal distribution at $\alpha/2$ (for a two-tailed test), Z_β is the critical value of the normal distribution at the desired power (β), δ is the expected effect size, and σ^2 is the variance within the population. For analyses involving correlations or regressions, sample size determination was informed by similar considerations but tailored to the specific statistical tests used. These calculations were guided by tools such as G*Power and consultation with statistical texts (Faul et al., 2019).

Based on a preliminary literature review and the expected effect size derived from similar studies, this study's desired sample size was 790, assuming a power of 90% and a significance level of 0.05. This sample size is deemed sufficient to detect the expected effects within the constraints of the study's design and objectives. Determining the sample size was a critical step in the research design, ensuring that the study is adequately powered to detect meaningful differences or relationships while considering practical limitations and ethical considerations. The calculated sample size supports the study's goals of producing reliable, valid, and generalizable findings that contribute meaningfully to the existing knowledge of AI in education. This meticulous approach to sample size determination underscores the rigour and thoughtfulness of the research methodology, setting a solid foundation for the subsequent data collection and analysis phases.

3.3.9 Methods of Analysis

The data gathered undergoes a rigorous analysis utilizing statistical techniques and machine learning algorithms, explicitly focusing on Support Vector Machine (SVM) modelling. SVM was employed to predict the impact of AI adoption on students' academic performance, considering the moderating factors of gender and geographical region.

Descriptive statistics is utilized to examine the demographic characteristics of the participants and the level of AI adoption in ODL. Inferential statistics, which encompass correlation analysis and structural equation modelling, were conducted to explore the relationships between AI adoption, academic performance, and moderating factors.

The SVM algorithm is employed to develop a predictive model that can anticipate the impact of AI adoption on students' academic performance. A model is developed to forecast students' academic performance based on AI adoption factors. The collected data are used to train and validate the model, and its performance is assessed using appropriate evaluation metrics. An SVM (Support Vector Machine) model is considered alongside Structural Equation Modeling (SEM) for several strategic reasons in this research:

I. **Different Focus:** SEM establishes and validates relationships between observed and latent variables. It is excellent for hypothesis testing and model fitting based on observed data. On the other hand, SVM is a machine-learning model primarily used for classification and regression. It focuses on predictive accuracy and generalization to new, unseen data.

II. **Predictive Accuracy:** SVM is renowned for its high predictive accuracy and ability to handle high-dimensional data spaces effectively. It can robustly manage non-linear relationships and interactions between variables, enhancing the model's predictive performance.

III. **Handling Non-linearity:** SVM can effectively manage non-linear relationships in the data through kernel functions, enabling the model to capture complex relationships and interactions, which SEM may not easily handle.

IV. **Robustness:** SVM is less sensitive to specification errors and is robust in noisy data. It is more focused on minimizing prediction errors, making it a robust tool in scenarios where prediction is key.

V. **Generalization:** SVM emphasizes the model's ability to generalize to new data, ensuring that the findings fit the sample data and apply to broader contexts.

VI. **Complementary Approach:** Using SVM alongside SEM allows for a complementary approach where SEM can help understand the underlying relationships and pathways. At the same time, SVM can enhance the predictive aspect, providing a well-rounded analysis.

VII. **Objective Alignment:** The research aims to develop a predictive framework. SVM aligns with this goal by offering a tool specifically designed for forecasting and prediction, complementing the insights derived from SEM.

By incorporating SVM alongside SEM, the research can leverage the strengths of both methodologies, combining SEM's capability in model fitting and hypothesis testing with SVM's robust predictive capabilities, ensuring a comprehensive and robust analysis aligned with the research objectives.

3.4 Tools used in the implementation

This section outlines the digital and analytical tools essential for the implementation of research. This section lists each tool used, comprehensively describing the tools' functions and their specific roles in the study context, as detailed in Table 3.1. The descriptions aim to elucidate the tools' contributions to data collection, analysis, or other research processes they facilitated. This allows for methodology transparency and offers readers insights into the practical aspects of the research's technical execution.

Table 3.1 Tools used in the implementation

S/N	Tool	Description of the Tool	How it is Used in the Research
1	Comprehensive Literature Review	Method for gathering existing knowledge	Identify factors affecting AI adoption and their effects on academic success in ODL contexts.
2	Visio, draw.io & Ludichart	Visualization tools for diagrams and charts	Crafting schematic diagrams during the design phase.
3	Unified Modeling Language (UML)	Language for specifying, visualizing, constructing, and documenting software systems	They are shaping the architecture of the process framework and overall research model.
4	Python	Object-oriented High-level programming language	The primary language for data analysis, especially within platforms like Anaconda Navigator and Jupyter Notebook
5	SVM Algorithm	A machine learning algorithm for classification and regression	Focus on prediction in the developed machine learning model.
6	Pandas, Numpy, Sklearn, matplotlib, and Imblearn	Libraries in Python for data analysis and visualization	Used with Python for data analysis, processing, visualization, and machine learning tasks.
7	Evaluation Metrics (Mean Squared Error, Mean Absolute Error, and Accuracy)	Evaluation metrics for machine learning models	These are the metrics to assess the integrity and effectiveness of the developed machine learning models.
8	Grammarly	Online writing and grammar checking tool	This was used to manage and check the quality of written content and ensure grammatical accuracy.
9	Citation Generator	Tool for generating citations in various formats	Managing citations throughout the research process.
10	Search Engine	Digital tools for finding specific information on the World Wide Web	Conducting additional background checks, referencing, and verification of sources
11	Questionnaire/Google Form	Tools to collect data from respondents, designed with structured queries	Gathering primary data, collecting responses related to the study's focus, and obtaining participant feedback or insights.
12	PowerPoint Deck	Tool for presenting the work to the supervisors, committees and International conferences	The work was laid out in PowerPoint slides and presented to the supervisors, committees and International conferences.
13	Smart PLS	Statistical analysis tool for carrying out data analysis using Structural Equation Modelling	The collected data was fed into Smart PLS and analysed using the defined research and structural equation models.

3.5 Approach and Techniques for the Proposed Solution

A detailed and structured approach is paramount to navigate the complexities and achieve this investigation's aims. This section delves into the methodologies and techniques to ensure the study's effectiveness. It narrates the meticulous planning and precise execution that underpin the research, from the initial conceptual framework to the refinement of specific algorithms. The narrative elucidates the progression from the initial concept to practical implementation, discussing the framework's design, the crafting of the model, the algorithm's development, and the formulation of the operational scheme. By dissecting these elements, the section offers a lucid exposition of the methodologies and strategies utilized, highlighting the exacting methods undertaken to realize the research's proposed solutions.

3.5.1 Design of Framework

To better elucidate the research objectives and the practical steps towards their realization, let us explore the intricacies involved in the 'Design of the framework' and how it serves to achieve these objectives:

Objective 1: Design a process framework incorporating the factors identified from the requirements to enhance understanding of AI adoption in Open Distance Learning (ODL).

Activity 1.1: A thorough systematic review of literature pertaining to AI integration in Online Distance Learning (ODL) was conducted. The focus was on identifying the determinants that propel the acceptance of artificial intelligence in such settings, examining the effect on students' academic performance, and understanding gender and geographical variances in AI adoption. This review draws from various sources, including electronic databases, academic journals, conference proceedings, and other pertinent materials. Studies aligning with the research objectives were selected using established inclusion and exclusion criteria. Data extracted from these studies were rigorously analyzed, providing a comprehensive perspective on the current state of AI adoption in ODL.

Activity 1.2: The inputs to this activity are the outputs from activities 1.1, 3.1 and 3.2. This activity involves designing the questionnaire and initiating and circulating an online questionnaire among ODL students. This online questionnaire captured data regarding AI adoption influencers, academic performance metrics, and essential demographic details. It employed a combination of text mining techniques and quantitative survey methodology via cluster sampling to collect data from student populations regarding their use of AI-based applications in the classroom. Cluster sampling was utilised to randomly select schools from each state, forming clusters and administering an online data collection form via Microsoft Forms. The instrument consisted of demographic data and data on factors influencing the developed conceptual model.

Activity 1.3: Develop a comprehensive process model that weaves in the factors discerned from the requirements elicitation phase, aiming to amplify insights into AI adoption within ODL settings. This model chronologically mapped out the key stages:

I. **Identification Phase:** Pinpoint the pivotal factors driving AI adoption in the ODL environment, emphasizing their interplay with student academic performance.

II. **Design and Validation Phase:** Design the research model and the process framework considering the dynamics of these factors and validate its representational accuracy.

III. **Implementation Phase:** Deploy machine learning techniques, capitalizing on gathered datasets, to predict how AI adoption determinants influence academic results.

IV. **Evaluation Phase:** Scrutinize the efficacy of the implemented system and machine learning models, ensuring they resonate with the primary aim of understanding AI's role in shaping academic outcomes in ODL.

This activity integrates the essence of the other objectives, particularly emphasizing the progression from requirements elicitation to evaluation, ensuring a holistic understanding of AI adoption's nuances in the ODL setting. All the other activities are inputs to activity 2.1.

Objective 2: Design a research model comprising the factors of AI adoption and student academic performance in ODL.

Activity 2.1: Construct a conceptual model using the core constructs of renowned theories - TAM, D&M, and UTAUT combined with specific factors inherent to the ODL context, refining them into eight primary independent variables. These variables are AI Alignment and Relevance (AAR), Comparative Advantage of AI (CAAI), Ease and Enjoyment of Use (EEU), AI Readiness and Facilitating Conditions (ARFC), AI-induced Learning Anxiety (AILA), Interactive Capability (IC), Knowledge Absorption and User Satisfaction (KAUS), Systems Quality and Social Influence (SQSI). These variables play a crucial role in shaping the adoption and application of AI technologies within the ODL framework, where students' academic performance is the main dependent outcome. Based on these, related hypotheses were established.

Activity 2.2: Furthermore, to provide a more comprehensive understanding, gender (G) and geographical location/region (R) were incorporated as moderating factors. This shows how gender and regional differences influence AI adoption within the ODL setting. The input to this activity is the output from activity 2.1.

Objective 3: Develop machine learning models to predict the impact of the identified factors of AI adoption on student academic performance.

Activity 3.1: Preprocess the received data from activity 2.3 to ensure its readiness for further scrutiny.

Activity 3.2: Utilized advanced algorithms, such as SVM, to construct a predictive model that correlates the determinants of AI adoption with academic outcomes. This model primarily focuses on understanding the relationship between AI adoption and student performance. Moreover, potential enhancements to the SVM algorithm were explored to improve its accuracy.

Activity 3.3: For more profound validation of the SVM outcomes achieved in Activity 4.1, apply structural equation modelling (SEM). This approach encompasses confirmatory factor analysis and validation, ensuring the alignment of SEM findings with the insights derived from machine learning. The machine learning model's outcomes are additionally validated through SEM analysis, thereby enhancing the credibility of the findings.

Activity 3.4: Analyzed the collected data to pinpoint the factors that drive AI adoption in ODL. This involved understanding the relationships between identified determinants and recognizing disparities in adoption based on gender and regional nuances. Subsequently, gauge the influence of these AI adoption drivers on students' academic performance, especially with respect to gender and regional variations.

Objective 4: Evaluated the machine learning models of AI adoption and student academic performance to establish the level of accuracy.

Activity 4.1: Evaluated the predictive model's performance by assessing various metrics, such as mean absolute error, Mean squared error, etc. The model's effectiveness was validated in predicting students' academic performance based on AI adoption.

Process Map: Understanding AI Adoption in ODL

An overview of the entire process framework is given in Figure 3.2, and more details are provided in section 3.4. The more detailed description of the process map for research as the whole is further elaborated below, detailing the description, inputs and outputs for each activity as follows:

Objective 1: Design a process model for AI adoption in ODL.

Activity 1.1: Systematic Review of AI in ODL Literature

- **Inputs:** Existing ODL literature, electronic databases, academic journals, conference proceedings, and other sources were thoroughly reviewed.
- **Outputs:** Identified the factors driving AI adoption, understanding of effects on students' academic performance, and understanding of gender and geographical variances.

Activity 1.2: Questionnaire Distribution and Data Collection

- **Inputs:** Findings from Activity 1.1, 3.1, and 3.2.
- **Outputs:** Data on AI adoption influencers, academic performance metrics, and essential demographic details were collected.

Activity 1.3: Process Model Development

- **Inputs:** Outputs from all other activities are the inputs.

- **Outputs:** A process model detailing the Identification, Design and validation, Implementation, and Evaluation phases.

Objective 2: Design a research model for AI adoption and academic performance in ODL.

Activity 2.1**:** Conceptual Model Creation

- **Inputs:** Established theories (TAM, D&M, UTAUT), ODL-specific factors.
- **Outputs:** Conceptual model with eight primary independent variables and their hypotheses.

Activity 2.2: Incorporation of Gender and Geographical Differences

- **Inputs:** Output from Activity 1.1.
- **Outputs:** Enhanced understanding of gender and geographical influence on AI adoption in ODL.

Objective 3: Develop predictive models for AI adoption's impact on academic performance.

Activity 3.1: Data Preprocessing

- **Inputs:** Data from Activity 2.3.
- **Outputs:** Cleaned and prepared data ready for analysis.

Activity 3.2: SVM Model Creation and Refinement

- **Inputs:** Processed data.
- **Outputs:** Predictive model, potential SVM enhancements.

Activity 3.3: Validation with SEM

- **Inputs:** SVM outcomes from Activity 4.1.
- **Outputs:** Validated findings through SEM.

Activity 3.4: Analyzing Collected Data

- **Inputs:** Collected data from previous activities.
- **Outputs:** Factors driving AI adoption, relationships between determinants, understanding of adoption disparities.

Objective 4: Evaluation of machine learning models.

Activity 4.1: Model Performance Evaluation

- **Inputs:** Predictive model's outcomes.
- **Outputs:** Evaluation metrics (accuracy, Error costs, etc.), validation of model's predictive power.

Figure 3.8. shows the process map for the designed Process Framework. The findings from the

research were synthesized, and the factors influencing AI adoption and their impact on academic performance in ODL were concluded. Based on the results, provide recommendations for designing and implementing effective AI-based interventions to enhance academic performance in ODL systems. By executing these activities systematically and cohesively, the research objectives outlined above can be achieved effectively. The resulting findings contribute to advancing knowledge in AI adoption in Online Distance Learning (ODL) and facilitate designing and implementing effective AI-based interventions to enhance academic performance in ODL systems.

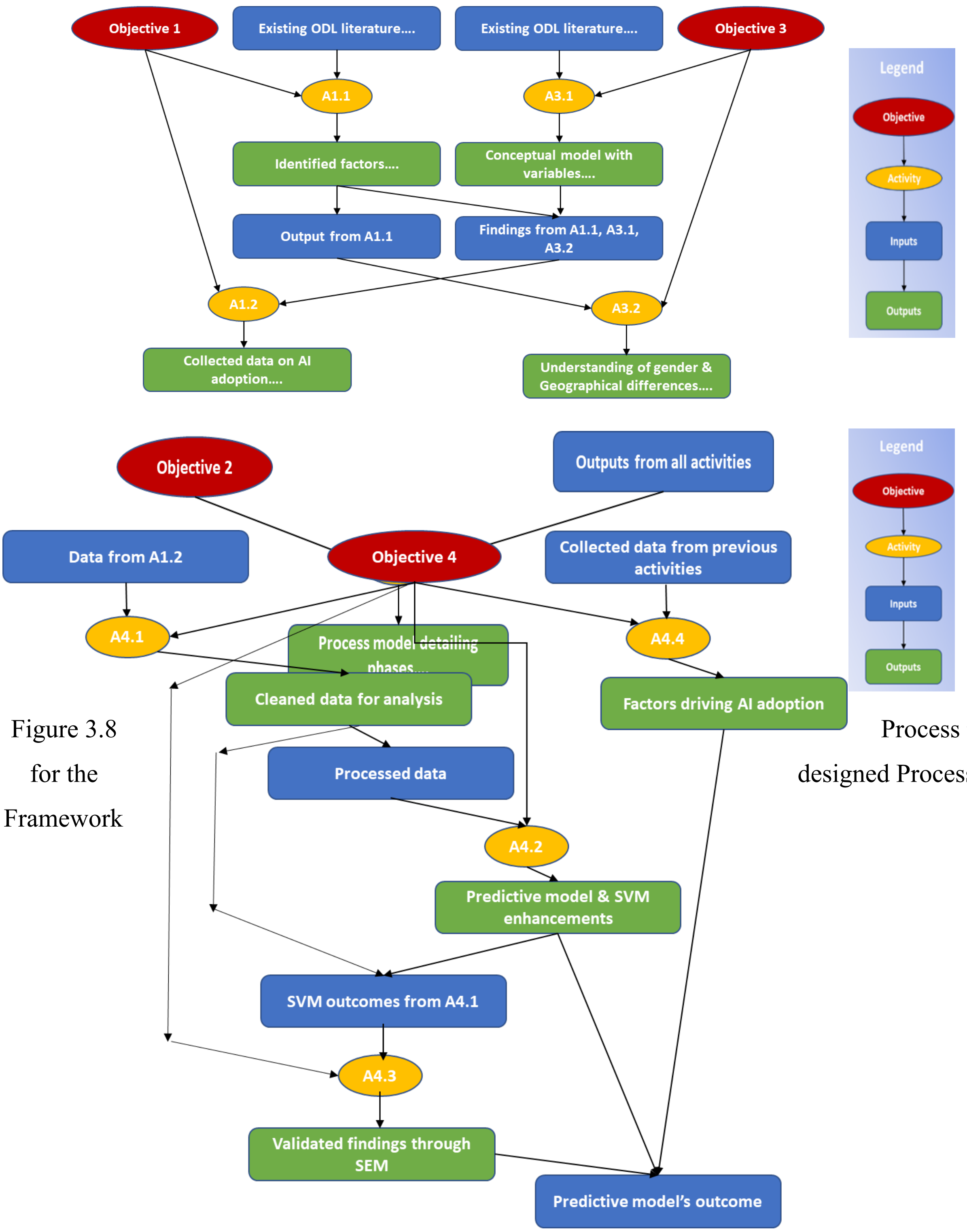
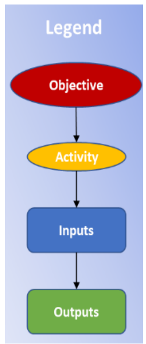


Figure 3.8 Process map for the designed Process Framework



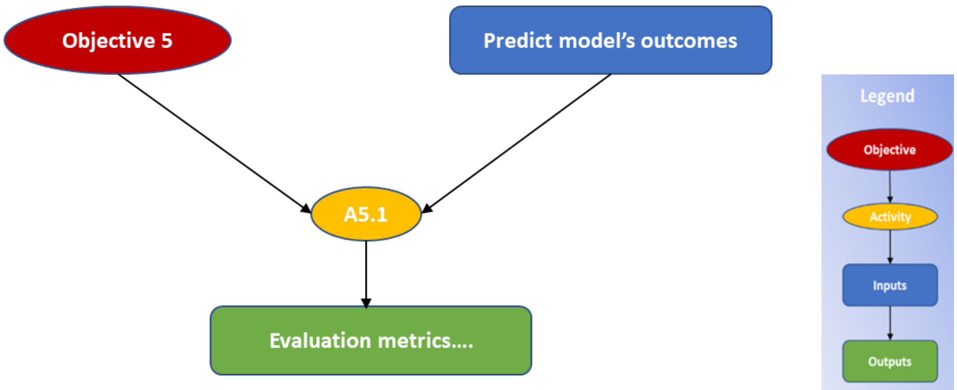


Figure 3.8 Process map for the designed Process Framework (Contd.)

This study aims to investigate the intricate relationship between AI adoption and students' academic performance in ODL settings. A predictive framework was developed by employing the SVM algorithm and integrating key constructs from established frameworks. Through comprehensive data collection, cluster sampling, and a machine learning modelling approach, this study seeks to provide valuable insights and inform effective interventions to enhance academic performance through AI adoption in ODL systems.

3.5.2 Formulation of model

This study combined the core constructs of renowned theories - TAM, D&M, and UTAUT- with specific factors inherent to the ODL context, refining them into eight primary independent variables. These variables, depicted in Figure 3.9, directly influence the implementation and utilisation of modern AI technologies in ODL settings, with students' academic performance as the dependent variable. The influence of these primary factors is further moderated by Gender(G) and Geographical Location/Region(R):

I. **AI Alignment and Relevance (AAR):** Measures AI's fit with student and institutional needs, integrating Institutional Alignment, Attitude toward Technology, and facets of Perceived Usefulness (Charness & Boot, 2016; Sabeh et al., 2021).
II. **Comparative Advantage of AI (CAAI):** Assesses the benefits of AI versus traditional methods, integrating Comparative Advantage and aspects of Perceived Usefulness (Yakubu & Dasuki, 2018).
III. **Ease and Enjoyment of Use (EEU):** Gauges AI use's simplicity and pleasure, blending Perceived Ease of Use and Perceived Enjoyment (Sabeh et al., 2021).
IV. **AI Readiness and Facilitating Conditions (ARFC):** Evaluates readiness for AI adoption and existing supportive conditions (Sabeh et al., 2021).
V. **AI-induced Learning Anxiety (AILA):** Determines the stress linked to AI-based learning.
VI. **Interactive Capability (IC):** It assesses preparedness for and enhancements in AI-facilitated online interactions (Charness & Boot, 2016; Sabeh et al., 2021).
VII. **Knowledge Absorption and User Satisfaction (KAUS):** Examines AI's impact on knowledge uptake and overall user contentment (Yakubu & Dasuki, 2018).
VIII. **Systems Quality and Social Influence (SQSI):** Evaluates AI system quality and the role of societal factors in its adoption (Sabeh et al., 2021; Yakubu & Dasuki, 2018).

This study presents a model blending constructs from prominent theories like the Technology Acceptance Model (TAM) - focusing on technology's ease of use and perceived usefulness (Charness & Boot, 2016); DeLone & McLean's Information Systems Success Model (D&M) - emphasizing system quality and user satisfaction (Sabeh et al., 2021); and the Unified Theory of Acceptance and Use of Technology (UTAUT) - assessing factors influencing technology acceptance, such as performance expectancy, effort expectancy, social influence, and facilitating conditions (Yakubu & Dasuki, 2018). Table 3.2 displays the research model's independent variables, which are formed by merging theoretical constructs with ODL-specific elements. These combined constructs constitute the model's independent variables.

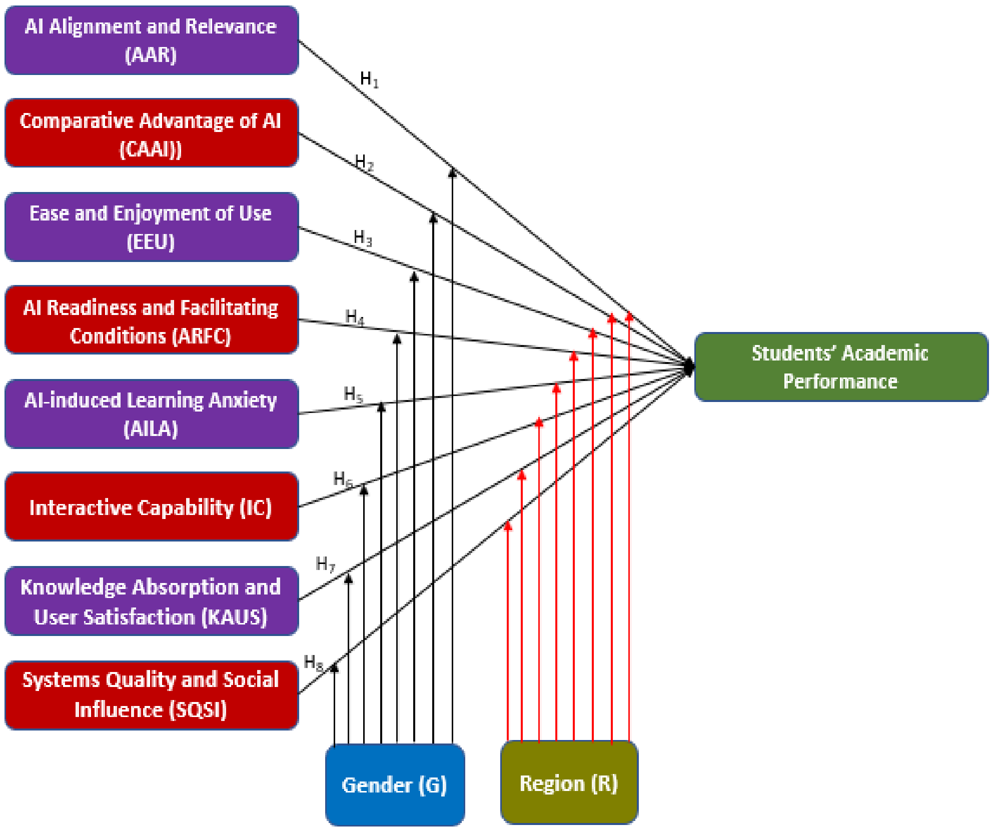


Figure 3.9 Research Model

The following Hypothesis H1, H2 to H8 were tested in this study:

I. H1: AI Alignment and Relevance (AAR) significantly impacts Students' academic performance prediction.

II. H2: Comparative Advantage of AI (CAAI) significantly impacts Students' academic performance prediction.

III. H3: Ease and Enjoyment of Use (EEU) significantly impacts Students' academic performance prediction.

IV. H4: AI Readiness and Facilitating Conditions (ARFC) significantly impacts Students' academic performance prediction.

V. H5: AI-induced Learning Anxiety (AILA) significantly impacts Students' academic performance prediction.

VI. H6: Interactive Capability (IC) significantly impacts Students' academic performance prediction.

VII. H7: Knowledge Absorption and User Satisfaction (KAUS) significantly impact Students' academic performance prediction.

VIII. H8: Systems Quality and Social Influence (SQSI) significantly impacts Students' academic performance prediction.

Table 3.2 Constructs of the newly formulated research model

S/N	Research model variables	Established Theories Constructs	Elements Unique to ODL
I	AI Alignment and Relevance (AAR) ***(Measures AI's fit with student and institutional needs)***	Attitude toward Technology (TAM) Facets of Perceived Usefulness (UTAUT)	Institutional Alignment
II	Comparative Advantage of AI (CAAI) ***(Assesses the benefits of AI versus traditional methods)***	Aspects of Perceived Usefulness (UTAUT)	Comparative Advantage
III	Ease and Enjoyment of Use (EEU) ***(Gauges AI use's simplicity and pleasure)***	Perceived Ease of Use (UTAUT) Perceived Enjoyment (UTAUT)	
IV	AI Readiness and Facilitating Conditions (ARFC) ***(Evaluates readiness for AI adoption and existing supportive conditions)***	Facilitating Conditions (UTAUT)	Readiness for AI adoption
V	AI-induced Learning Anxiety (AILA) ***(Determines the stress linked to AI-based learning)***		Stress linked to AI-based learning.
VI	Interactive Capability (IC) ***(Assesses preparedness for and enhancements in AI-facilitated online interactions)***	Aspect of perceived usefulness (TAM) Perceived Ease of Use (UTAUT)	Preparedness for online interactions Impact on group collaboration
VII	Knowledge Absorption and User Satisfaction (KAUS) ***(Examines AI's impact on knowledge uptake and overall user contentment)***	User Satisfaction (D&M Model)	Impact on knowledge uptake
VIII	Systems Quality and Social Influence (SQSI ***(Evaluates AI system quality and the role of societal factors in its adoption.)***	AI system quality (D&M Model) Social Influence (UTAUT)	

3.5.3 Development of algorithm

Modifications to the SVM algorithm were made to handle the nature of the questionnaire data, which consists of ordinal data with responses such as "Strongly Disagree," "Disagree," etc. Categorical variables were encoded to ensure suitability for the SVM model, which expects numerical input.

In this context, ordinal encoding is a commonly used preprocessing technique where each unique category value is assigned an integer value. The encoding for the Likert scale data follows the pattern in Table 3.3.

Table 3.3 Likert scale data encoding

S/N	Questionnaire values	Encoded values
1.	Strongly Disagree	1
2.	Disagree	2
3.	Neither Agree nor Disagree	3
4.	Agree	4
5.	Strongly Agree	5

This encoding preserves the inherent order in the categories, ranging from "Strongly Disagree" to "Strongly Agree," enabling the SVM to process the questionnaire data accurately.
However, it is essential to acknowledge that although the data is ordinal, the distances between points on the Likert scale may not represent equal changes in sentiment. Therefore, this preprocessing step is combined with exploratory data analysis to understand better the response distributions and their relationship to the outcome variable.

Additionally, the code is adjusted to identify and handle missing data in the survey responses. An appropriate strategy replaces the missing data by taking the averages of the other responses for each construct. This step ensures the integrity of the data used in the SVM model. The modifications made the data preprocessing steps feed into the SVM (Support Vector Machine) algorithm:

- **Load Data:** The raw dataset is loaded into the memory. It is typically loaded into a data frame in pandas, which allows data manipulation.
- **Ordinal Encoding:** The Likert scale responses in the dataset are converted to numerical values using ordinal encoding. This is important because the SVM algorithm requires numerical input.
- **Handle Missing Data:** Missing values are handled by replacing them with the average of the corresponding construct's responses. This ensures the SVM algorithm gets a complete dataset without missing values, which could distort the model's training and results.
- **Compute Composite Scores:** The composite scores for each construct are calculated by taking the mean of the associated items. These scores serve as the final values for each construct used as input for the SVM model.
- **Verify Internal Consistency:** Internal consistency is checked using Cronbach's Alpha. Although this does not directly feed into the SVM algorithm, it is a crucial step to ensure the reliability of the constructs.
- **Data Preparation for SVM:** The dataset has various AI-related constructs as the independent

variables (features) and Students' Academic Performance as the dependent variable (target). This arrangement of data is the form that is expected by the SVM algorithm.

- **Train-Test Split:** The dataset is split into training and test sets. The training set is used to train the SVM model, while the test set is used to evaluate the model's performance.

The rest of the steps include training and evaluating the SVM model. Performing T-tests and performing distribution, correlation, and chi-square analyses do not directly feed into the SVM algorithm but are used for understanding the model's performance and the relationships between different variables. The SVM algorithm takes the preprocessed data (features and target variable) and tries to find a hyperplane in the multi-dimensional space that distinctly classifies the data points. After training the SVM model, it can predict the target variable (Students' Academic Performance) for new data. Figure 3.10 shows the area of machine learning that was implemented with the chosen algorithm. The focus was on supervised machine learning utilizing regression tasks.

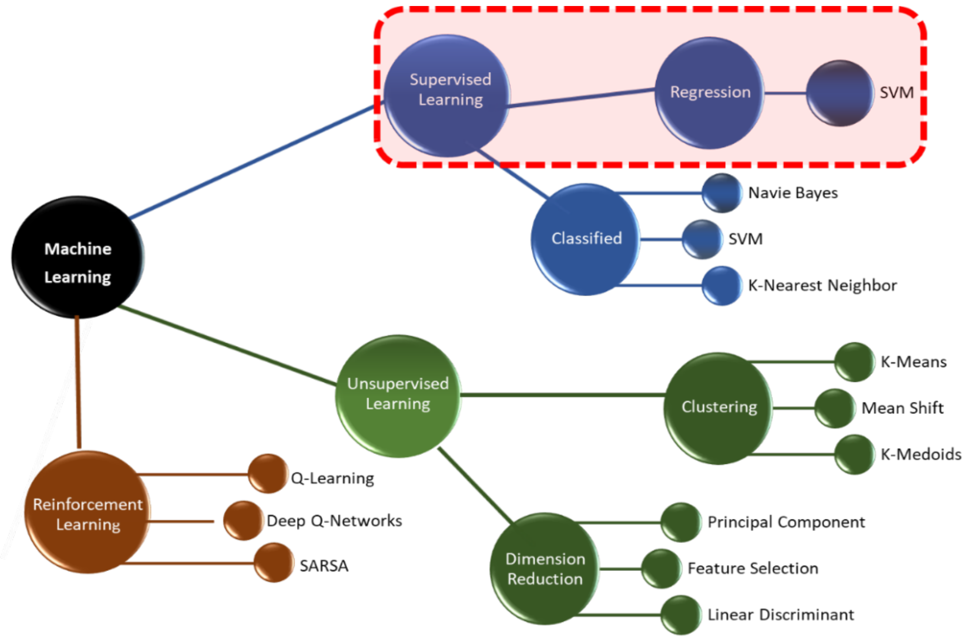


Figure 3.10 Areas of Machine Learning Treated in this Research

In order to optimise the Support Vector Machine (SVM) model, extensive efforts were undertaken to adjust key parameters and explore kernel combinations. These initiatives were aimed at enhancing model accuracy. The regularization parameter (C) and the kernel parameter (gamma) were rigorously adjusted. The regularization parameter was meticulously calibrated to balance the trade-off between securing a minimal-margin hyperplane and reducing training error. Concurrently, the gamma parameter was tuned to regulate the Radial Basis Function (RBF) kernel's width, which is crucial for determining the model's flexibility around data points.

Various methods, including grid search, cross-validation, and gradient descent, were employed to identify the optimal settings for these parameters. These methods facilitated a systematic evaluation of different combinations of C and gamma, using cross-validation techniques to ensure stable performance across various data subsets. Additionally, the model's sophistication was further explored through kernel combination techniques. Combinations such as Linear plus RBF and Polynomial plus RBF were tested, integrating the straightforward decision boundaries of linear models with the nuanced adaptability of RBF kernels. Multiple Kernel Learning (MKL) was also applied to find an effective blend of these kernels, specifically tailored to the problem's unique characteristics. Despite these efforts, the enhancements from parameter tuning and kernel combinations did not yield the anticipated improvements in accuracy. The SVM model outperformed the configurations resulting from these advanced techniques with its default settings using the RBF kernel. As a result, further effort was made to employ the AdaBoost algorithm.

Adopting AdaBoost, which utilises a sequence of weak learners to form a robust predictive model, did not improve the accuracy of the SVM model. The integration of AdaBoost with the support vector regression framework, leveraging its default parameterisation, did not achieve notable gains in predictive performance. This outcome highlighted the limitations of AdaBoost in this context, underscoring that adaptive boosting techniques may not always lead to superior accuracy, especially when conventional parameter optimisation and kernel customisation strategies fall short. Despite the theoretical benefits of combining SVM's capability to handle high-dimensional data and AdaBoost's ability to identify and emphasise informative training samples, the actual implementation did not result in improved accuracy. This suggests that the AdaBoost-SVM ensemble was unable to capture the underlying patterns and relationships in the data, emphasising the need for further exploration of ensemble methods and adaptive boosting techniques in machine learning.

3.5.3 Development of the scheme

This section discusses the development of a comprehensive evaluation scheme for the AI-based Moodle platform. The evaluation scheme is meticulously designed to assess the platform's efficacy and user experience through a structured survey. This survey is divided into distinct constructs to ensure a holistic platform assessment. Key constructs include Interactive Capability (IC), Knowledge Absorption and User Satisfaction (KAUS), and Systems Quality and Social Influence (SQSI). Each construct is informed by a combination of theoretical models, such as the Unified Theory of Acceptance and Use of Technology (UTAUT) and the Technology Acceptance Model (TAM), and tailored to evaluate specific aspects of the Moodle platform relevant to Open and Distance Learning (ODL).

I. Demographics - Section A:

- This section is designated to collect basic demographic information from respondents, which is crucial for contextualizing the study's findings and understanding the diversity of the participant pool.
- The demographics captured include age groups, allowing for analysis across different life stages and gender identification, providing insights into gender-specific responses, especially since gender is considered a moderating factor in the study.
- Additionally, geographical location is collected to focus on understanding the impact of cultural and regional differences on the adoption and effectiveness of AI in education. The study pays particular attention to Canada and Nigeria, considering geographical location as another moderating factor.
- The field of study also includes technical disciplines like computer science and information technology and broader fields such as social sciences and humanities. This helps assess AI's penetration and perceived impact across various academic disciplines.
- By analyzing these demographic variables, the research aims to identify patterns and correlations between these factors and the adoption and outcomes of AI-based learning, thus enriching the interpretation of the research model's results.

II. AI Alignment and Relevance (AAR) - Section B:

- This construct assesses the congruence between the AI-based Moodle platform, students' learning objectives, and the institution's educational goals.
- Items inquire about the platform's alignment with individual and institutional learning needs and its relevance to course content.
- The construct is influenced by elements specific to Open and Distance Learning (ODL) for assessing institutional alignment. It draws upon the UTAUT model for Perceived Usefulness and the TAM model for Attitude toward Technology.

III. Comparative Advantage of AI (CAAI) - Section C:

- This section evaluates the perceived benefits of the AI-based Moodle platform over traditional learning methods.
- Questions aim to understand the advantages of the platform's effectiveness and efficiency to the learning process.
- The construct is informed by unique ODL elements concerning Comparative Advantage and utilizes the UTAUT model to gauge Perceived Usefulness.

IV. Ease and Enjoyment of Use (EEU) - Section D:

- This construct explores the usability and user experience associated with the AI-based

Moodle platform.

- Items cover ease of use, enjoyment, intuitiveness, and user engagement with the platform.
- It incorporates the UTAUT model's concepts of Perceived Ease of Use and Perceived Enjoyment to measure the user experience.

V. AI Readiness and Facilitating Conditions (ARFC) - Section E:

- This segment investigates the preparedness of both students and institutions to adopt the AI-based Moodle platform.
- Items assess the readiness for AI adoption and the extent of support for using the platform effectively.
- The construct is based on the unique requirements of ODL for readiness assessment and includes the UTAUT model's Facilitating Conditions to evaluate support mechanisms.

VI. AI-induced Learning Anxiety (AILA) - Section F:

- This construct is designed to measure the levels of anxiety and stress that students may experience when using the AI-based Moodle platform for learning.
- The items in this section address students' concerns, such as the stress of using new technology, worries about depending solely on the AI-based platform for educational purposes, feeling overwhelmed by its complexity, and concerns about potential negative impacts on learning outcomes due to technical problems.
- The origin of these items stems from the specific attributes and challenges associated with Open and Distance Learning (ODL), focusing mainly on the stressors linked to integrating AI into learning environments.
- By examining these elements, the research aims to identify how anxiety is induced by using AI in educational settings and how this might affect students' overall learning experience.

VII. Interactive Capability (IC) - Section G:

- This construct gauges the platform's role in fostering online interaction and collaboration.
- Questions in this section probe students' preparedness to engage online and the platform's enhancement of interactions with teachers and peers.
- Another significant facet is the platform's impact on group collaborations and how effectively it aids communication within the learning environment.
- The items are informed by models like UTAUT, which focuses on effort expectancy and incorporates elements peculiar to ODL to evaluate the impact on group collaboration. They also drew from the TAM model, emphasizing Perceived Usefulness.

VIII. Knowledge Absorption and User Satisfaction (KAUS) - Section H:

- This segment assesses how the platform affects students' understanding and assimilation of course content.

- Questions delve into the satisfaction levels stemming from using the platform and its role in elucidating complex course material.
- While some items are based on the D&M Model, focusing on User Satisfaction, others highlight the platform's impact on knowledge uptake, derived from elements unique to ODL.

IX. Systems Quality and Social Influence (SQSI) - Section I:

- Here, the emphasis is on the technical quality of the AI-based Moodle platform and the social factors influencing its adoption.
- Respondents reflect on the platform's reliability, speed, design, and overall quality.
- Social determinants that impact the platform's acceptance, including peer views and external discussions (e.g., on social media), are explored.
- Questions in this category are informed by the D&M Model, which emphasizes System Quality, and the UTAUT model, which spotlights Social Influence.

X. Students' Academic Performance - Section J:

- This construct evaluates students' perceptions of the impact of AI tools on their academic achievements within an online learning environment.
- The items in this section ask students to reflect on their beliefs regarding the influence of AI on their academic performance, understanding of course materials, contribution to their grades, and overall academic improvement.
- The construct, as perceived by the students, is critical in understanding the tangible outcomes of implementing AI in online learning. It is integral to assessing the overall success of AI adoption in educational settings.

This scheme's systematic design endeavours to comprehensively assess the AI-based Moodle platform, capturing varied dimensions of user experience and system efficacy. Table 3.4 shows the Questionnaire items used to measure the constructs of the newly formulated research model. The actual questionnaire is shown in Appendix B. Each item in the table is carefully constructed to measure specific constructs and is sourced from established models in the literature, ensuring a robust framework for analyzing the impact of the AI-based Moodle platform on learning outcomes.

Table 3.4 Questionnaire items used to measure the constructs of the newly formulated research model

Independent Variable	Item number	Items	Source	Constructs measured
AI Alignment and Relevance (AAR)	Section B	1. I feel that the AI-based Moodle platform used in my course aligns well with my learning needs and objectives.	Elements Peculiar to ODL	Institutional Alignment
		2. The AI-based Moodle platform implemented in my institution aligns with its educational goals and values.	Elements Peculiar to ODL	Institutional Alignment
		3. The use of AI-based Moodle platform features makes my course content more relevant.	UTAUT	Perceived Usefulness
		4. Using the AI-based Moodle platform in my course positively impacts my attitude towards technology in education.	TAM	Attitude toward Technology
Comparative Advantage of AI (CAAI)	Section C	1. Learning with the AI-based Moodle platform is more effective than traditional educational methods.	Elements Peculiar to ODL	Comparative Advantage
		2. The AI-based Moodle platform features provide significant advantages to my learning process compared to traditional methods.	Elements Peculiar to ODL	Comparative Advantage
		3. Learning with the AI-based Moodle platform is more efficient in terms of time and resource utilization.	UTAUT	Perceived Usefulness
		4. The AI-based Moodle platform enhances the effectiveness of my learning outcomes compared to traditional methods.	UTAUT	Perceived Usefulness
Ease and Enjoyment of Use (EEU)	Section D	1. I find it easy to use the AI-based Moodle platform for learning in my course.	UTAUT	Perceived Ease of Use
		2. My experience interacting with the AI-based Moodle platform in my course is enjoyable.	UTAUT	Perceived Enjoyment
		3. Learning with the AI-based Moodle platform is intuitive and user-friendly.	UTAUT	Perceived Ease of Use
		4. The use of the AI-based Moodle platform in my course is engaging and motivating.	UTAUT	Perceived Enjoyment
AI Readiness and Facilitating Conditions (ARFC)	Section E	1. I feel well-prepared to use the AI-based Moodle platform in my learning.	Elements Peculiar to ODL	Readiness for AI adoption
		2. My institution is well-prepared for adopting and implementing the AI-based Moodle platform.	Elements Peculiar to ODL	Readiness for AI adoption
		3. I receive substantial support (technical, learning resources, etc.) in using the AI-based Moodle platform for learning.	UTAUT	Facilitating Conditions
		4. The conditions in my institution facilitate the effective use of the AI-based Moodle platform for learning.	UTAUT	Facilitating Conditions

Table 3.4 Questionnaire items used to measure the constructs of the newly formulated research model (Contd.)

Independent Variable	**Item number**	**Items**	**Source**	**Constructs measured**
AI-induced Learning Anxiety (AILA)	Section F	1. I often feel anxious or stressed about using the AI-based Moodle platform in my course.	Elements Peculiar to ODL	Stress linked to AI-based learning.
		2. I feel worried about relying on the AI-based Moodle platform for learning.	Elements Peculiar to ODL	Stress linked to AI-based learning.
		3. I often feel overwhelmed by the complexity of the AI-based Moodle platform used in my course.	Elements Peculiar to ODL	Stress linked to AI-based learning.
		4. I worry that errors or problems in the AI-based Moodle platform could negatively impact my learning outcomes.	Elements Peculiar to ODL	Stress linked to AI-based learning.
Interactive Capability (IC)	Section G	1. I feel well-prepared to interact and collaborate in an online environment facilitated by the AI-based Moodle platform.	Elements Peculiar to ODL	Preparedness for online interactions
		2. The AI-based Moodle platform has enhanced my ability to interact with teachers and peers.	TAM	Perceived usefulness
		3. The use of the AI-based Moodle platform has positively impacted my collaboration in group projects or activities.	Elements Peculiar to ODL	Impact on group collaboration
		4. The AI-based Moodle platform facilitates effective communication in my learning environment.	UTAUT	Perceived Ease of Use
Knowledge Absorption and User Satisfaction (KAUS)	Section H	1. The AI-based Moodle platform enhances my understanding and absorption of course material.	Elements Peculiar to ODL	Impact on knowledge uptake
		2. I am satisfied with my learning outcomes due to the use of the AI-based Moodle platform.	D&M Model	User Satisfaction
		3. The AI-based Moodle platform often aids in clarifying complex course material or concepts.	Elements Peculiar to ODL	Impact on knowledge uptake
		4. The use of the AI-based Moodle platform improves my satisfaction with the learning experience.	D&M Model	User Satisfaction
Systems Quality and Social Influence (SQSI)	Section I	1. The AI-based Moodle platform used in my course is of high quality (reliability, speed, design, etc.).	D&M Model	System Quality
		2. The views of my peers significantly influence my usage of the AI-based Moodle platform in my course.	UTAUT	Social Influence
		3. Social media, discussions with peers, or instructors' opinions have a strong impact on my acceptance and use of the AI-based Moodle platform.	UTAUT	Social Influence
		4. High-quality AI systems enhance their acceptance and use among my peers.	D&M Model	System Quality

3.6 Research Design Including Research Process Unified Modelling Language (UML)

Integrating AI in educational settings, particularly in ODL, necessitates a robust and comprehensive research methodology. The research design combines qualitative and quantitative approaches to ensure a thorough exploration of AI's impact on student performance. The study employs UML as a tool to visually represent the research process, thereby clarifying the relationships between different study components. The research design includes a detailed literature review, framework development, and empirical validation using machine learning algorithms like Support Vector Machine (SVM) and Structural Equation Modeling (SEM).

3.6.1 Research Design.

The research design ensures a systematic approach to achieving the aim and objectives. It integrates qualitative and quantitative paradigms to ensure comprehensive data collection, analysis, and validation. This study thoroughly explored and consolidated scholarly articles regarding using artificial intelligence (AI) in educational environments, explicitly examining its influence on students' learning outcomes. The main aim was to conduct an in-depth systematic analysis of existing literature, identifying key elements and theoretical models pertinent to integrating AI in educational settings. The goal was to develop a comprehensive procedural framework and a predictive analysis model to evaluate AI's impact on student performance in Open and Distance Learning (ODL) systems.

I. **Strategy for Literature Search** An extensive literature search was conducted across renowned academic databases, including Google Scholar, Scopus, and Web of Science, using a combination of keywords such as "Artificial Intelligence" or "AI", "student performance" or "academic outcomes", and "adoption factors" or "integration", to encompass a wide range of pertinent academic works.

II. **Criteria for Selecting Literature**

Inclusion Criteria:

- This study includes peer-reviewed articles and conference papers discussing AI in ODL contexts.
- This study includes works examining AI adoption theories, models, or frameworks in education.
- This study includes recent articles (published within the last eight years) in English for contemporary relevance.

Exclusion Criteria:

- This study includes articles and conference papers that are not peer-reviewed or academic.
- Studies are not focused on AI integration in ODL environments.

III. **Method of Data Aggregation For each chosen publication**:

- Recording the authors and year of publication.
- Pinpointing the objectives or research questions.
- Summarizing key findings, especially regarding factors influencing AI adoption.
- Highlighting any notable frameworks, models, or theories mentioned.

After completing the literature review, the project moved into a design phase, applying a systematic method to ensure the new models were practical and relevant. The comprehensive literature analysis identified key themes and principles, which were then used as the foundation for developing the process framework and research model. Mind mapping and conceptual modelling helped visualise and organise these elements, ensuring their theoretical consistency and logical flow, particularly in how they relate to AI's impact on student performance.

i. **Core Component Identification**: Key elements influencing AI adoption and its impact on learning outcomes were identified from the literature review and used as the basis for the new design.
ii. **Framework Development**: Insights from the literature were used to create an initial framework draft, outlining the relationships and sequence of the core elements, from AI adoption factors to their effects on academic results.
iii. **Model Development**: A detailed research model was then developed, specifying the variables, their relationships, and theoretical foundations, aiming to provide a comprehensive view of how AI adoption affects academic performance.
iv. **Evaluation and Improvement**: The initial framework and model were repeatedly refined, aligned with the literature, and adjusted for clarity and coherence. This included checking for inconsistencies and gaps and ensuring the designs were comprehensive and coherent.
v. **Tool Selection for Visualization**: Tools such as Lucidchart and Microsoft Visio were chosen for their ability to clearly and effectively represent the process framework and research model, ensuring the designs were both scholarly and user-friendly.

Expanding the research design to include empirical validation of the framework and research model in ODL settings, SVM, improved SVM, and SEM were utilized to analyze real-world data from ODL environments using these machine-learning algorithms. Their accuracy assesses the effectiveness of these models in predicting student outcomes and their ability to handle complex data structures.

i. **Empirical Data Acquisition**: Data were systematically collected from ODL settings, concentrating on the variables delineated within the framework.
ii. **Implementation of Machine Learning Techniques**: Student performance was predicted based on the identified variables by utilizing SVM and improved SVM. SEM was utilized to corroborate the interrelations among these variables.

iii. **Evaluation of Algorithms**: The performance of SVM, enhanced SVM, and SEM was evaluated through metrics such as accuracy, precision, and the capability to model intricate relationships.

iv. **Comparative Examination**: A thorough analysis of the merits and demerits of each algorithm was conducted within the ODL context to ascertain the most efficacious strategy for predicting and comprehending student performance in these educational settings.

This methodology guarantees a thorough validation of the research model and framework, yielding a rigorous analysis of the influence of artificial intelligence on academic outcomes within the domain of ODL.

3.6.2 Discussion of Research Activities in UML

I. Designing the Process Framework

This focuses on establishing a foundational process model through a systematic literature review, data collection, and model development. The literature review identifies critical factors influencing AI adoption and its effects on academic performance, while data collection gathers quantitative evidence. The process model is then developed to provide a blueprint for subsequent activities. UML diagrams, aligned with the first objective, represent the framework components that encapsulate the factors influencing AI adoption in ODL. Activity diagrams showcase the flow of processes, ensuring a clear understanding of AI's role in ODL.

Activity diagram: This activity diagram represents a simplified flow of processes in understanding and mapping the factors influencing AI adoption to their roles in ODL. The process flow of AI adoption in ODL is illustrated in Figure 3.11, which showcases the sequential steps involved from initial engagement to the outcome.

II. Constructing the Research Model

This objective involves creating a conceptual model that links established theories with the unique aspects of ODL. It culminates in a comprehensive model with hypotheses ready for empirical testing. Gender and geographical differences are also considered, enhancing the model's complexity and depth. Use case diagrams or class diagrams to illustrate the various factors of AI adoption and their potential impact on student performance. This ensures a comprehensive model encapsulating all relevant entities and their interrelations.

Class diagram: a class diagram representing the entities related to AI adoption factors and their impact on student performance. This class diagram illustrates two main entities: AI Adoption Factors and Student Performance. The association between them indicates that multiple AI adoption factors can impact various attributes of student performance. Figure 3.12 presents the class diagram, which details the relationship between various AI adoption factors and their impact on student performance.

III. Machine Learning Model Development

In this stage, the focus is on the technical development of predictive models. Data preprocessing ensures the quality and relevance of the data, SVM model creation seeks predictive accuracy, and SEM validation confirms the model's robustness. Sequence and state diagrams illustrate the progression from data collection and preprocessing to model training using SVM. These diagrams provide insight into the machine learning lifecycle, emphasizing the interaction between AI adoption factors and prediction algorithms.

State Diagram: This represents the different states in the machine learning lifecycle. This state diagram represents the machine learning lifecycle from data collection to model evaluation. The state diagram in Figure 3.13 represents the various stages in the machine learning lifecycle, from data collection to model evaluation.

Sequence Diagram: Figure 3.14 demonstrates the sequence diagram, outlining the steps involved in training and evaluating the SVM model.

IV. Evaluation of the Machine Learning Model

The evaluation phase is highlighted through UML's activity diagrams, detailing the steps taken to validate the SVM model's accuracy in predicting academic performance based on AI adoption factors. The evaluation phase of the SVM model is detailed in Figure 3.15, which uses a UML activity diagram to elucidate the validation steps. The overall system architecture for the SVM-based process framework is depicted in Figure 3.16, illustrating the interconnected modules and their functions.

V. Comparative Analysis of Machine Learning Models

The comparative analysis phase is designed to assess the efficacy of different machine learning models, specifically the SVM, Improved SVM, and Structural Equation Models (SEM), in predicting academic performance influenced by AI adoption factors. This phase is crucial for determining the most effective model for practical applications within ODL settings.

The UML activity diagrams illustrate the series of actions undertaken to compare the performance of the traditional SVM model against its improved version and the SEM. These diagrams detail the processes involved in evaluating each model's accuracy, the handling of data, the application of statistical methods for validation, and the criteria used for performance comparison.

The activity diagrams outline the steps of data preprocessing, model training, hyperparameter tuning, and cross-validation for the SVM and Improved SVM models. For the SEM, the diagrams depict the processes of specifying the model, estimating parameters, and assessing the model's fit.

In addition, the UML class diagrams are employed to represent the structural relationships between the different models and the constructs they aim to predict. These diagrams show how each model encapsulates various performance metrics and how they relate to the underlying AI adoption factors.

Sequence diagrams further elaborate on the interactions between the researcher, the models, and the evaluation system, showing the sequential order of operations leading to the comparative analysis.

State diagrams describe each model's different states during the evaluation process, from initialization to the final state, where the models are either accepted or refined based on comparative results.

The comparative analysis culminates in a comprehensive understanding of each model's strengths and limitations, providing clear guidance on which model offers the most reliable predictions for academic performance in the context of AI adoption in ODL. The findings from this comparative analysis are synthesized into the overall system architecture diagram, depicted in Figure 3.16, which illustrates the interconnected modules responsible for evaluating, comparing, and selecting the machine learning models. This system architecture facilitates a holistic view of the comparative analysis within the broader framework of the study.

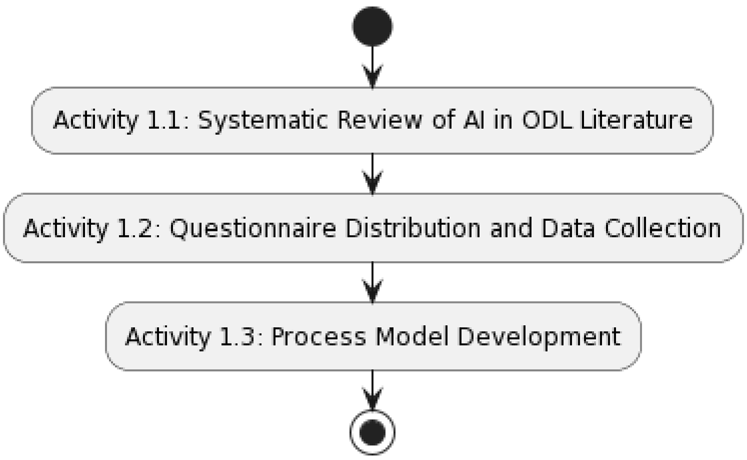
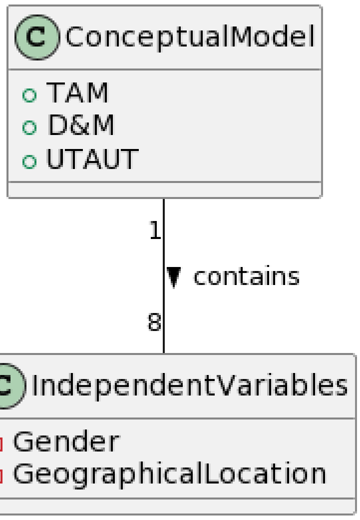


Figure 3.11 Activity Diagram of AI Adoption in ODL Process Flow



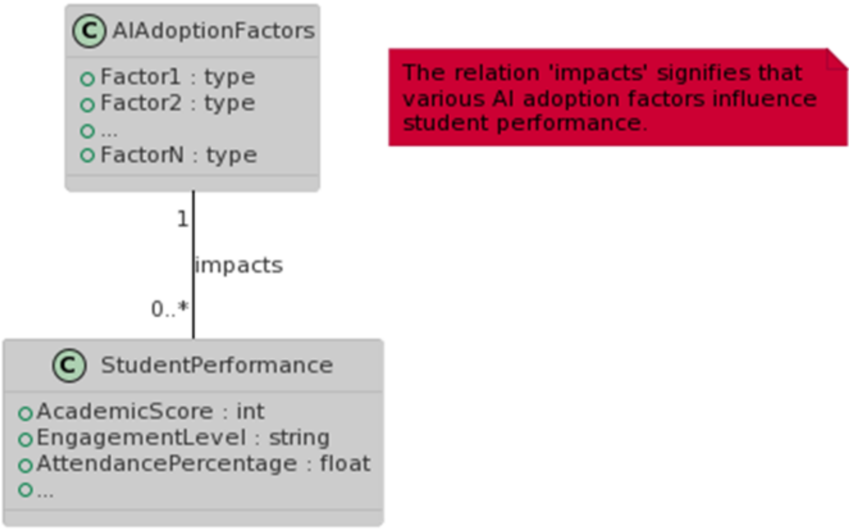


Figure 3.12 Class Diagram of AI Adoption Factors and Student Performance

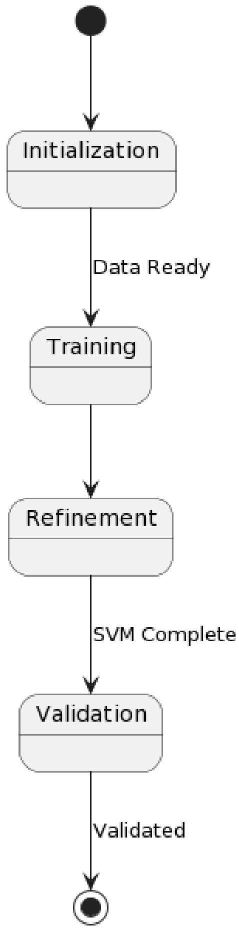


Figure 3.13 State Diagram of Machine Learning Lifecycle in SVM Model

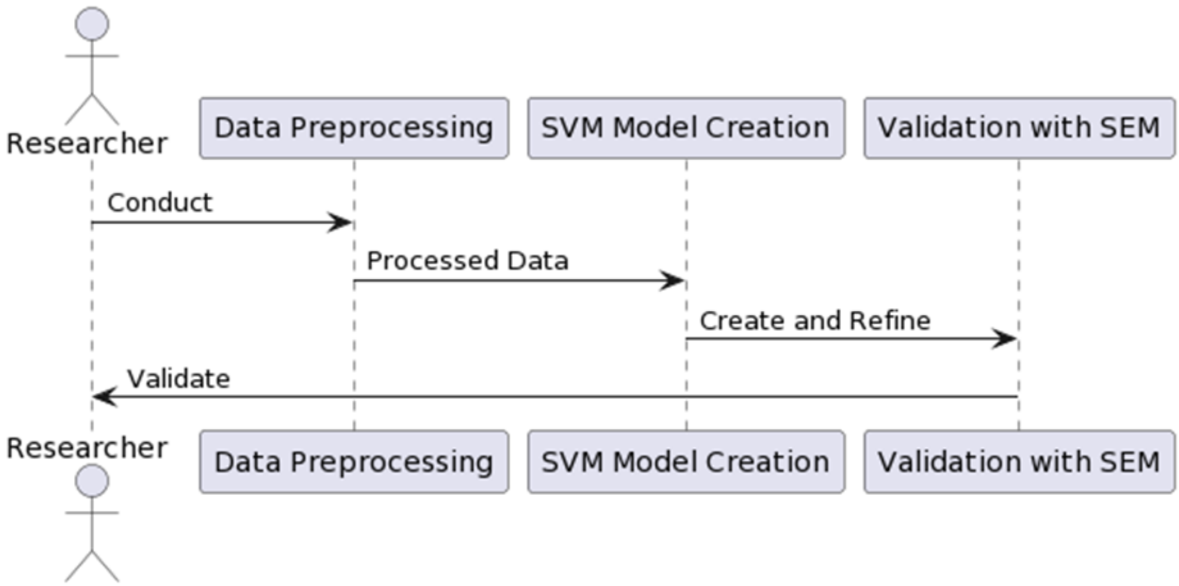


Figure 3.14 Sequence Diagram for SVM Model Training and Evaluation

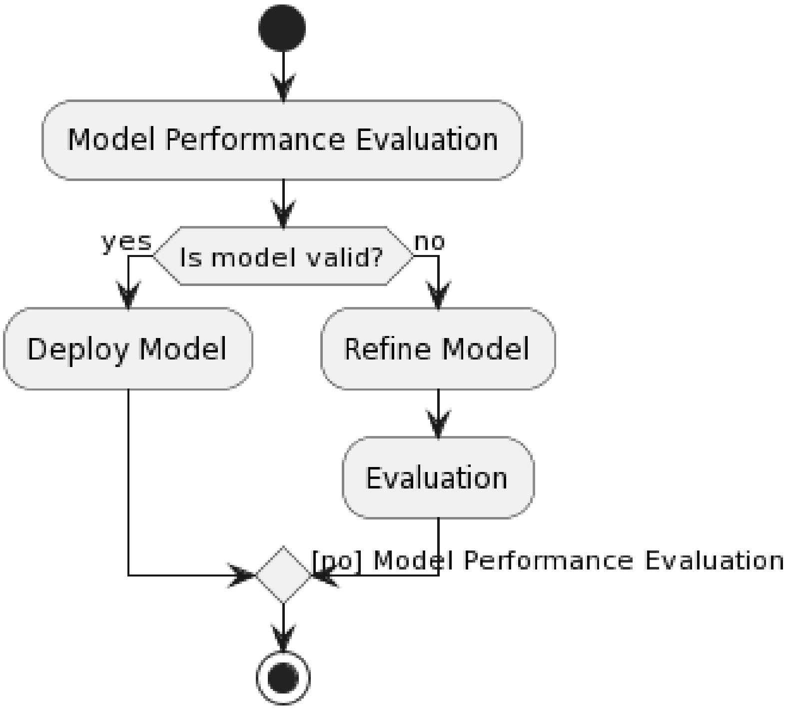


Figure 3.15 UML Activity Diagram for SVM Model Evaluation

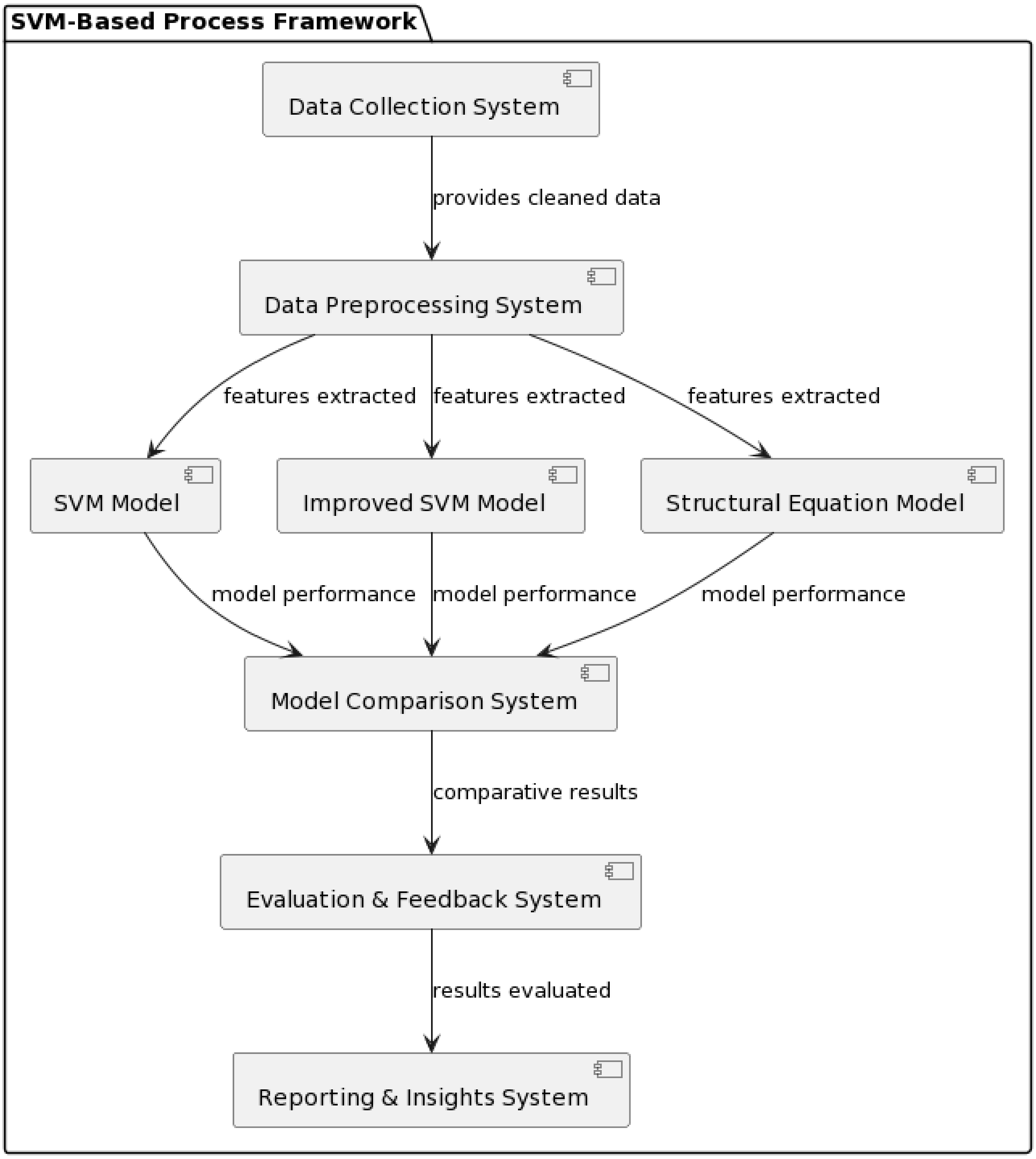


Figure 3.16 System Architecture Diagram using UML diagrams for SVM-Based Process Framework

3.7 Description of Validation Techniques for Proposed Solution

This section delves into the methodologies for validating the proposed machine learning-based solution. The validation process encompasses multiple steps, from dataset collection and characterization to the final simulation procedures. Exploratory Data Analysis (EDA) is utilized for dataset validation to understand the underlying structure and distribution of the data. Feature Engineering is employed to refine the dataset for the SVM model, ensuring that only relevant and impactful features are included. Subsequently, rigorous machine learning model validation is conducted, which includes a Train-Test Split, Cross-Validation, and Hyperparameter Tuning, ensuring the model's robustness and accuracy. Lastly, Simulation Procedures are implemented to assess the model's real-world applicability, followed by a Feedback Loop for continuous model refinement based on real-world data. This comprehensive approach ensures the solution's theoretical soundness and practical applicability in predicting the impact of AI adoption on student performance in ODL settings.

I. **Dataset Collection and Description:**

- **Source of Collection**: The data was primarily gathered from the literature to guide the research model formulation, while an online Google form questionnaire was used to collect data from the ODL students about their perspective on using an AI-based Moodle platform. The specificity of the study necessitates the collection of new data, as existing datasets are not tailored to assess the intricate impact of Moodle's AI tools on student academic performance in ODL settings. The research focuses on the Moodle platform, which is integral to ODL environments and is grounded in literature as the most assessed AI solution for AI adoption.
- **Description and Cleaning**: Each dataset comprises attributes ranging from student demographics to interaction metrics with online content. It was imperative to clean and preprocess the data, removing any inconsistencies and missing values that might skew the subsequent analyses. The SVM algorithm was modified to cater for the missing values.

II. **Validation of Questionnaire:**

- **Pre-testing**: Before the widespread distribution of the questionnaire, it underwent pre-testing with a select group. Feedback was collated, and necessary modifications were implemented to ensure clarity and relevance.
- **Reliability Analysis**: Cronbach's alpha was used to determine the internal consistency of the questionnaire. An alpha value above 0.7 was considered acceptable, indicating that the questions were consistently interpreted. Cronbach's alpha procedure was introduced into

the SVM algorithm as part of what must be carried out before model building. Although this does not directly feed into the SVM algorithm, it is a crucial step to ensure the reliability of the constructs. This improves the overall efficiency of the data pre-processing.

- **Factor Analysis**: Employed to identify underlying structures or patterns in the questionnaire responses, ensuring that each factor or component derived was meaningful and interpretable.

III. **Dataset Validation:**

- **Exploratory Data Analysis (EDA)**: Preliminary assessments using EDA helped in understanding the underlying structure of the data, its distribution, and potential relationships between variables.
- **Feature Engineering**: Relevant features were extracted, created, or selected based on their potential significance to the model's predictive power.

IV. **Machine Learning Model Validation:**

- **Train-Test Split**: The dataset was split into training and testing sets. The training set is used to train the model, while the testing set is reserved to evaluate its performance. An 80/20 split was used in this case.
- **Cross-Validation**: Techniques like 5-fold cross-validation were employed. This involves partitioning the dataset into '5' subsets. The model is trained on 5-1 subsets and tested on the remaining one. This process is repeated five times, rotating the test set to provide a comprehensive evaluation.
- **Hyperparameter Tuning**: The best parameters for the model were determined using methods like grid search or random search.
- **Performance Metrics**: The nature of the problem is regression. Appropriate metrics, such as Mean Squared Error and Mean Absolute Error, were used to gauge the model's effectiveness.
- **Model Interpretability**: Appropriate guides and instructions were provided to interpret and understand the model's decision-making process, ensuring transparency and trust in the predictions.

V. **Real-World Applicability:**

- **Simulation Procedures**: Simulations were conducted to understand the solution's practical implications, replicating real-world scenarios and assessing how the solution would perform under various conditions.

- **Feedback Loop**: Post-deployment, a feedback mechanism was established. This allowed for continuous monitoring and iterative solution refinement based on real-world feedback.

The journey from data collection to deploying a machine-learning solution is replete with meticulous validation steps. Each phase ensures the solution is theoretically sound and poised for practical, real-world application.

3.8 Description of Performance Evaluation Parameters/Metrics

This section outlines the metrics and parameters used to evaluate the performance of the developed machine learning models. The primary metrics include Mean Absolute Error (MAE), Mean Square Error (MSE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Normalized Mean Square Error (NMSE). The 5-fold Cross-Validation method is applied to each metric to ensure a comprehensive assessment of the model's performance. This approach provides a holistic view of the model's accuracy and reliability and helps mitigate the risk of overfitting, thereby enhancing the model's generalizability. The developed models are evaluated using the following performance metrics (Equations 17-22), which have been adapted from Adewale et al. (2024), Aftarczuk (2007) and Bajaj (2023):

Mean Absolute Error (MAE) = $\frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right|$ (22)

Mean Square Error (MSE) = $\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2$ (23)

Root Mean Square Error (RMSE) = $\sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}$ (24)

Where y_i and $\hat{y}_i$ are the actual and predicted values $\overline{y}_i$ is the mean value of y_i. The smaller the error values, the closer the predicted values are to the actual values. This is accomplished using the 5-fold cross-validation (5-fold CV) method. This method, which helps avoid overfitting and gives a more accurate test error estimate, divides the data into five randomly selected folds. The model is trained on the remaining four folds during each iteration, with the one-fold serving as a validation set. This process is repeated five times, each iteration using a different fold as the validation set. The MAE, MSE, MAPE, RMSE, and NMSE are computed for each fold. The MAEs, MSEs, MAPEs, RMSEs, and NMSEs are averaged to produce the final 5-fold CV estimate (Equations 23-27). Every metric offers a unique perspective on the model's performance and is valuable in various situations. It is essential to consider a wide range of evaluation metrics to compare and decide on models. The models' performance can be assessed on various subsets of the data using the 5-fold cross-validation approach, which provides a more accurate estimate of the model's generalizability, as adapted from Pandian (2023).

$$CV_{(5)mae} = \frac{1}{5}\sum_{i=1}^{5} MAE_i \tag{25}$$

$$CV_{(5)mse} = \frac{1}{5}\sum_{i=1}^{5} MSE_i \tag{26}$$

$$CV_{(5)rmse} = \frac{1}{5}\sum_{i=1}^{5} RMSE_i \tag{27}$$

By enabling us to select the ideal cost function, the 5-fold CV evaluation of MAE, MSE, MAPE, RMSE, and NMSE also balances the trade-off between bias and variance in model selection. This prevents overfitting (where a model fits the training data too closely and struggles to generalize to new data). A 5-fold CV offers a way to enhance model performance and guarantee accurate predictions in this way.

In the context of Structural Equation Modeling (SEM), metrics like Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) are not typically used as they are in predictive modelling (e.g., regression, machine learning models). SEM focuses on understanding the relationships between observed and latent variables, assessing model fit, and testing theoretical constructs rather than making predictions about individual data points.

For SEM, the emphasis is on model fit indices that tell us how well the specified model reproduces the observed data. Some of the common fit indices used to evaluate SEM models include:

I. **Chi-Square Test of Model Fit (χ^2)**: This is a statistical test to compare the model-implied covariance matrix with the observed covariance matrix. A non-significant chi-square value indicates that the model fits the data well, but this test is sensitive to sample size (Lai, 2020).

II. **Root Mean Square Error of Approximation (RMSEA)**: Estimates lack of fit in a model compared to a perfect model. Values of RMSEA ≤ 0.05 indicate a close fit, values up to 0.08 represent a reasonable error of approximation, and values greater than 0.10 suggest a poor fit (Xia & Yang, 2018).

III. **Comparative Fit Index (CFI)** and **Tucker-Lewis Index (TLI)**: These indices compare the specified model to a baseline model, typically a null model in which all observed variables are uncorrelated. Values closer to 1 indicate a good fit, with values ≥ 0.95 often considered indicative of a well-fitting model (Shi et al., 2021).

IV. **Standardized Root Mean Square Residual (SRMR)**: This is the average discrepancy between the observed correlations and the model's predicted correlations. Values less than 0.08 are generally considered good (Shi & Maydeu-Olivares, 2020).

These and other fit indices provide a comprehensive assessment of how well the proposed SEM model represents the structure of the observed data. Unlike MAE or RMSE, which assess accuracy on a case-by-case basis, SEM fit indices evaluate the overall coherence of the model structure with the empirical data, focusing on the relationships and interactions among variables rather than prediction accuracy.

Validating the results of SVM predictive modelling with Structural Equation Modeling (SEM) results involves comparing insights from both approaches to see if they align in terms of the importance and relationships between variables. While SEM and SVM serve different primary purposes (theory testing and confirmation for SEM, prediction for SVM), insights from SEM can provide a theoretical basis for understanding the relationships that SVM models capitalize on for prediction. Here is how SEM results can be used to validate and interpret SVM predictive modelling results:

I. Understanding Variable Relationships:

- **SEM** helps identify and confirm the hypothesized relationships between independent variables (IVs) and dependent variables (DVs) and among the IVs themselves. It provides a comprehensive view of how variables relate to each other, including direct, indirect, and mediated relationships.
- **SVM** results, particularly the feature importances in linear SVM or insights from techniques like permutation importance for non-linear SVM, indicate which variables are most predictive of the outcome.
- **Validation:** If SEM indicates strong relationships between certain IVs and the DV, and these IVs also appear as important predictors in SVM, this consistency validates the SVM model's reliance on theoretically grounded relationships.

II. Examining Direct and Indirect Effects:

- **SEM** can dissect complex relationships by quantifying direct, indirect, and total effects among variables. This nuanced understanding can highlight variables that influence DV through mediated pathways.
- **Validation:** SVM lacks the native ability to differentiate between direct and indirect effects. However, suppose SEM shows that certain variables have strong total effects (direct + indirect) on the DV, and these variables are also important in SVM predictions. In that case, it suggests the SVM model is capturing meaningful patterns that align with the theoretical framework established by SEM.

III. Incorporating Latent Variables:

- **SEM** often includes latent variables representing constructs measured indirectly through multiple observed variables. These constructs can provide a deeper understanding of the phenomena under study.
- **Validation:** While SVM directly uses observed variables or latent constructs, understanding the latent constructs from SEM can provide context for interpreting the SVM results. For example, suppose a latent construct validated by SEM is represented by a set of observed variables or latent constructs that are significant in SVM. In that case, it supports the relevance of this construct in predicting the DV.

IV. Model Fit and Predictive Accuracy:

- **SEM** provides fit indices (e.g., RMSEA, CFI, SRMR) that evaluate how well the model captures the relationships in the data.
- **SVM** is evaluated through predictive accuracy metrics (e.g., MAE, RMSE, accuracy score).
- **Validation:** While these metrics assess different aspects (theoretical fit vs. predictive accuracy), an SEM model with good fit indices suggests the theoretical model is plausible. An SVM model with high predictive accuracy, based on variables and relationships confirmed by SEM, suggests that these theoretically grounded relationships are also predictive in new data.

V. Cross-Validation with Different Data Sets:

- Conduct SEM and SVM on different subsets of the data or entirely new datasets. Consistency in the relationships and variable importance across SEM and SVM analyses further validate the findings.

While SEM and SVM have distinct objectives and methodologies, combining insights derived from both methodologies can offer a robust framework for comprehending and forecasting intricate phenomena. The theoretical substantiation of relationships and constructs provided by SEM can enhance the credibility of the predictive patterns recognized by SVM, particularly when the significance of variables in SVM corresponds with the established relationships validated by SEM. This cross-validation approach enriches the interpretation of SVM results, grounding them in a tested theoretical framework.

3.9 System Architecture for the SVM-Based Process Framework for Predicting Students' Academic Performance in Open and Distance Learning

The system architecture aims to understand and predict the impact of AI adoption on students' academic performance in Open Distance Learning (ODL) environments. By leveraging a series of interconnected modules and subsystems, the architecture is designed to harness data, process it, model predictions, and evaluate these predictions to improve the effectiveness of AI adoption in ODL. The system is designed to streamline research, from gathering data to evaluating predictive models. It integrates various modules, such as data collection, preprocessing, analysis, machine learning, and validation. Figure 3.17 presents a streamlined components-based system architecture diagram, mapping out the structured flow and interconnection of various components within the system. The architecture begins with the Data Collection System (DCS), which comprises modules for literature review and questionnaire management, essential for gathering initial data. Following data collection, the Research Model Formulation (RMF) component is tasked with constructing the conceptual framework for the study. The subsequent Data Preprocessing System (DPS) is pivotal for cleaning data and ensuring uniformity through normalization or standardization, as well as for selecting the most impactful features for modelling. The Modeling & Analysis System (MAS) then takes centre stage, developing and refining predictive models, validating their outcomes, and conducting factor analysis to identify key drivers.

The performance of these models is meticulously evaluated in the Model Evaluation System (MES) using a variety of statistical metrics. Finally, the Reporting & Insights System (RIS) brings the process to a close by transforming the analyzed data into actionable insights through interactive dashboards and visualizations, thereby completing the system's end-to-end flow from data collection to decision-making insights. The system architecture is designed to predict the impact of AI adoption on students' academic performance in ODL environments. It consists of interconnected modules such as data collection, preprocessing, analysis, machine learning, and validation. The architecture aims to streamline the research process from gathering data to evaluating predictive models. Key components include the Data Collection System (DCS), Data Preprocessing System (DPS), Research Model Formulation (RMF), Modeling and Analysis System (MAS), Evaluation and Feedback System (EFS), and Reporting and Insights System (RIS). Each of these components plays a vital role in ensuring the efficacy of the AI-based Moodle platform.

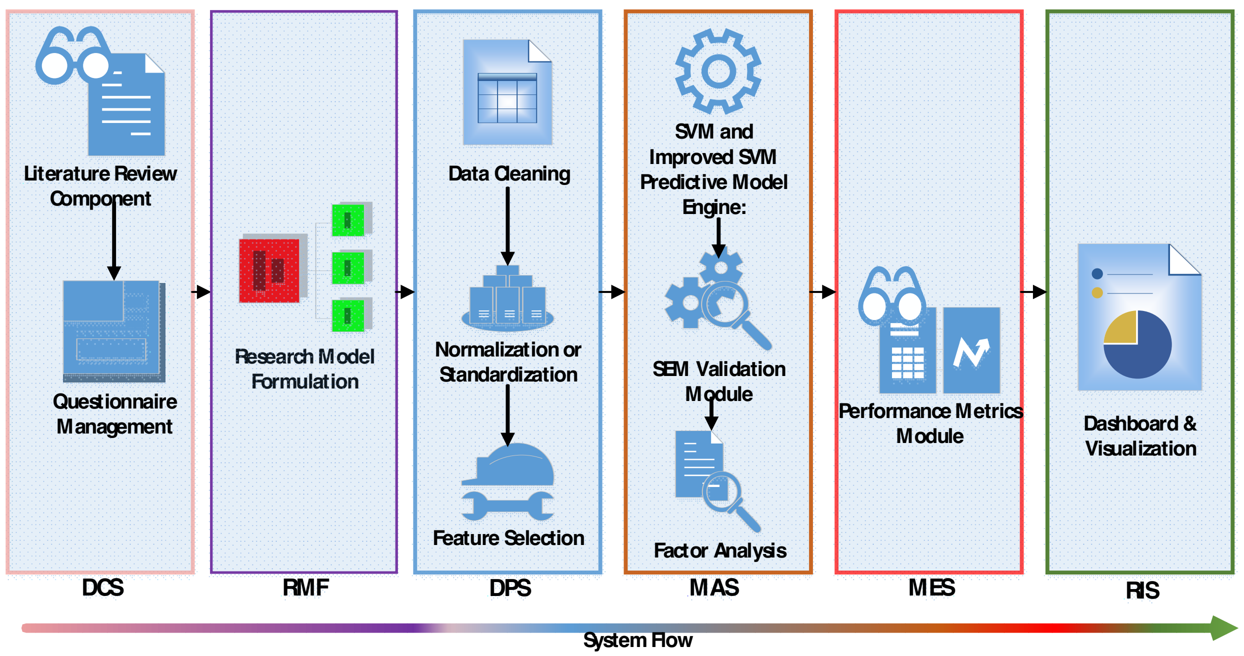


Figure 3.17 Simple System Architecture for Support Vector Machine-Based Process Framework for Predicting Students' Academic Performance in Open and Distance Learning

3.9.1 Architecture Components

The system architecture can be conceptualized into the following main components:

I. **Data Collection System (DCS)**

a. **Literature Review Module**: Gathers and synthesizes data from academic journals, electronic databases, and other academic sources.

b. **Questionnaire Management**: Facilitates the distribution, retrieval, and initial processing of questionnaires distributed among ODL students.

II. **Data Preprocessing System (DPS)**

The integrity and quality of data form the bedrock of predictive analytics. The DPS is the critical phase where raw data is sculpted into a pristine dataset primed for analysis. This system is composed of several pivotal subprocesses that collectively enhance the data's suitability for the modelling tasks ahead:

a. **Data Cleaning Module**: Removes anomalies, inconsistencies, and irrelevant entries from the collected data. The first gatekeeper of data quality, this module rigorously scans the dataset to identify and excise anomalies, inconsistencies, and extraneous entries. From correcting mislabeled categories to addressing missing values, this process ensures that the remaining dataset is accurate, reliable, and devoid of any distortions that could skew the analytical results.

b. **Normalization & Standardization Procedure**: Ensures the dataset maintains a uniform scale and structure. With the data cleansed, this procedure eliminates any biases arising from disparate data scales and distributions. Normalizing and standardizing the dataset establishes a common ground where all features can contribute equally to the predictive models, uninfluenced by their original scales. This uniformity is vital for algorithms that are sensitive to the scale of input data, ensuring that each variable's influence is purely based on its inherent predictive power rather than its magnitude.

c. **Feature Selection**: Beyond cleaning and scaling, the DPS employs a discerning feature selection mechanism to pinpoint the variables that significantly impact the outcome of interest. This mechanism employs feature selection techniques to evaluate the predictive utility of each variable, retaining those that offer meaningful contributions to the model's accuracy and discarding those that do not. This selective process not only enhances model performance but also streamlines the complexity of the model, leading to faster computation and more interpretable results.

The DPS transforms raw, unstructured data into a refined, analysis-ready form by meticulously executing these preprocessing steps. This well-curated dataset is a solid foundation for the subsequent modelling and analysis, setting the stage for insightful and actionable predictions.

III. **Research Model Formulation (RMF)**

At the heart of the system architecture, the Research Model Formulation is the strategic phase where the study's conceptual framework is established. This component's research model is meticulously crafted, setting the stage for subsequent data analysis and insight generation. The core activities within this phase include:

a. **Conceptual Framework Development:** The RMF begins with developing a conceptual framework that outlines the hypothesized relationships between various factors under study. This framework serves as the blueprint for the research, guiding the selection of variables and the direction of analyses.

b. **Variable Designation:** In this critical step, variables are carefully selected and designated roles within the research model:

- Independent Variables: These are the factors believed to influence or predict the outcome of interest. They are chosen based on literature review findings, theoretical relevance, and practical considerations.
- Dependent Variable: This is the primary outcome variable that the research

seeks to explain or predict. It is identified based on the research objectives and the effectiveness of the independent variables against which they are measured.

c. **Hypothesis Formulation:** Clear and testable hypotheses are formulated based on the conceptual framework. These hypotheses posit the expected relationships and effects of the independent variables on the dependent variable.

d. **Model Specification:** The research model is specified by selecting appropriate statistical or machine learning methods that align with the research objectives and the nature of the data. This includes determining the model structure, interaction terms, and potential moderating or mediating variables.

e. **Operationalization of Variables**: Operationalization involves defining how the model measures and represents the variables. This includes identifying the measurement scales, coding categorical variables, and ensuring the variables are operationalized in ways consistent with the research hypotheses.

f. **Analytical Techniques Selection:** The RMF also entails choosing the proper analytical techniques that best suit the data and the research questions. This could range from regression analysis for continuous outcomes to classification techniques for categorical outcomes, with considerations for the complexity of the model and the computational resources available.

By carefully formulating the research model, the RMF system sets a solid foundation for the Modelling and Analysis System (MAS) to perform rigorous data analysis, ultimately leading to valid and actionable insights represented through the Reporting and insights System (RIS).

IV. **Modelling & Analysis System (MAS)**

a. **SVM and Improved SVM Predictive Model Engine**: Constructs and refines the SVM model and Improved SVM for predicting student performance based on AI adoption. The Support Vector Machine (SVM) engine, an advanced algorithm renowned for its classification precision, is at the forefront of this system. This engine is tasked with constructing a foundational SVM model and is also charged with enhancing it, leading to an 'Improved SVM'. This iterative process involves refining the SVM's kernel functions, regularization parameters, and other hyperparameters to adapt to the nuances of predicting student performance influenced by Artificial Intelligence (AI) adoption in Online Distance Learning (ODL).

b. **SEM Validation Module**: Validates SVM outcomes and offers insights into the relationships between AI adoption and performance. Parallel to the model construction, the Structural Equation Modeling (SEM) Validation Module is a critical evaluator of the SVM's predictive outcomes. By employing SEM, the module provides a multi-faceted analysis that validates the SVM model's predictions and offers a deeper understanding of the intricate relationships between AI adoption and student performance. This validation is critical to ensuring that the model's insights are statistically significant and hold substantive weight in educational theory and practice.

c. **Factor Analysis**: Identifies and ranks factors that drive AI adoption in ODL, further analyzing relationships and disparities. Complementing the SEM Validation, the Factor Analysis sub-system delves into the myriad variables influencing AI adoption in ODL. This analytical process meticulously identifies and ranks the factors according to their impact and relevance. Through exploratory and confirmatory techniques, the Factor Analysis uncovers underlying patterns, elucidates the direct and indirect relationships among variables, and highlights possible disparities. This rigorous investigation informs further model refinements and contributes to a holistic understanding of AI's role in shaping educational outcomes.

The MAS is an integral cog in the machine, ensuring that the data yields accurate predictions and imparts interpretative value that stakeholders can translate into actionable strategies. It is where data science meets domain expertise, resulting in a robust, validated model that stakeholders can trust for strategic decision-making.

V. **Model Evaluation System (MES):**

The Model Evaluation System is deployed to assure excellence and precision, operating as the arbiter of performance and effectiveness. This system encompasses:

a. **Performance Metrics Module**: Assesses predictive model outcomes through metrics like MAE, MSE, RMSE, RRSE, and R^2. A robust module that meticulously assesses the outcomes of the predictive models. Utilizing a battery of statistical measures—Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Root Relative Squared Error (RRSE), and the coefficient of determination (R^2)—the module quantifies the models' performance. These metrics offer a comprehensive view of the model's accuracy, consistency, and predictive power, serving as benchmarks for optimization.

VI. **Reporting & Insights System (RIS)**

The culmination of the predictive analysis is manifested in the Reporting & Insights System, a platform where data stories are told with clarity and impact. This system comprises:

a. **Dashboard & Visualization**: Presents findings and insights in a user-friendly and interactive manner. With a user-centric design ethos at its core, this module presents the analytical findings through a series of interactive and intuitive dashboards. By distilling complex data patterns into visual narratives, the dashboards facilitate the engaging exploration of insights, empowering stakeholders to grasp the nuances of the data swiftly. Interactive charts, graphs, and maps provide a multi-dimensional view of the findings, fostering an environment conducive to informed decision-making and strategic foresight.

Through these systems, the architecture ensures the rigour and reliability of predictive modelling and guarantees that the insights derived are accessible, actionable, and grounded in empirical evidence. The MES and RIS form a continuous feedback loop where insights lead to actions, and outcomes circle back as inputs for further model refinement.

3.9.2 System Flow

I. The system's journey commences with the meticulous gathering of data, engaging academic sources through a robust Literature Review Module, paralleled by the systematic acquisition of primary data via a comprehensive Questionnaire Management system. The system initiates with data collection, leveraging both academic sources (through the Literature Review Module) and primary data (via the Questionnaire Management system).

II. After the initial data collection, the Research Model Formulation is activated to chart the course for the ensuing predictive modelling. This integral phase strategically selects variables and constructs a theoretical scaffold to underpin predictive analytics. The Research Model is formulated to guide the development of predictive models.

III. After advancing from model formulation, the data is channelled through a sequence of preprocessing steps. This phase is instrumental in refining the raw data through cleansing, normalization, and feature selection, setting the stage for accurate and meaningful analysis. The gathered data undergoes a series of preprocessing steps to prepare it for modelling.

IV. Upon cleansing, the data is ushered into the Modeling and Analysis System (MAS), which is sculpted into predictive models. These models are honed and validated against the framework established by the RMF, ensuring that the predictions are accurate and reflect the research intent. The MAS uses the processed data to build, refine, and validate the predictive models.

V. Once predictions are made, the system evaluates its effectiveness, identifying areas of improvement. The predictions rendered by the models are then subjected to a rigorous effectiveness assessment. This crucial evaluation, carried out by the Model Evaluation System (MES), pinpoints the models' performance, spotlighting opportunities for refinement and enhancement.

VI. Culminating the system's flow, the Reporting & Insights System (RIS) captures the essence of the analyzed data, translating complex models and metrics into digestible visualizations and cogent recommendations. This system ensures stakeholders have clear, actionable insights, driving informed decisions. Findings, visualizations, and recommendations are presented to stakeholders through the RIS.

3.10 Ethical considerations

This research undergoes a thorough ethical review by a designated committee to ensure adherence to the highest ethical standards before fieldwork begins. The University Ethics Committee Approval is in Appendix C. The submission for this review includes a detailed explanation of the methodology, objectives, benefits, and potential risks to participants, emphasizing our commitment to conducting a study that respects participant dignity, rights, and welfare. Critical aspects addressed in the ethical considerations include:

I. **Informed Consent**: Participants receive comprehensive information about the research, enabling them to make informed decisions regarding their involvement. Consent is obtained voluntarily, free from any form of coercion.

II. **Confidentiality and Anonymity**: Participants' identities and personal information are protected through anonymization and secure data storage. The dissemination of findings excludes any personally identifiable information.

III. **Risk Assessment**: The study identifies and minimizes potential physical and psychological risks to participants, ensuring minimal discomfort.

IV. **Data Protection and Privacy**: The research adheres to data protection laws, ensuring privacy and security of participant data through careful handling and storage in compliance with legal and institutional policies.

V. **Ethical Research Design**: The research design and methodology meet ethical standards, ensuring integrity and participant welfare.

VI. **Compliance with Laws and Guidelines**: The research aligns with all relevant laws, regulations, and institutional guidelines related to ethical research.

VII. **Addressing Unforeseen Ethical Issues**: Procedures are in place to manage unexpected ethical issues that may arise during the research.

VIII. **Privacy and Data Security:** In designing the SVM-based framework, paramount importance is placed on student data privacy and security. This study adopts comprehensive encryption protocols and adheres to the most stringent data protection laws, including the General Data Protection Regulation (GDPR), to safeguard sensitive student information. Anonymization techniques are utilized to remove any identifiable markers from data sets before analysis, ensuring that individual students cannot be identified from the results, thereby upholding the principle of confidentiality in educational data handling.

IX. **Bias Mitigation and Equity:** The study employs a multi-faceted approach to address and mitigate bias within the AI model. Initial steps involve curating diverse data sets that reflect varied student backgrounds, ensuring that a wide range informs the model's learning phase of experiences and performance outcomes. Additionally, regular bias audits are conducted throughout the model training process to identify and correct any skewed predictions that could disadvantage specific student groups. This proactive stance on bias mitigation is crucial for fostering an equitable learning environment where every student can benefit from AI-enhanced educational experiences.

X. **Legal and Regulatory Compliance:** The SVM-based process framework is developed with strict adherence to existing legal and educational policy frameworks. This commitment extends beyond mere compliance; it involves active engagement with legal experts and educational authorities to ensure that the model aligns with current regulations and emerging standards in AI governance. This approach ensures that the framework remains a viable and compliant tool for enhancing student outcomes in ODL settings.

XI. **Responsible AI Use and Societal Values:** The methodology emphasizes the responsible use of AI, where the technology acts as an augmentative tool rather than a replacement for human educators. To align the AI framework with societal values, stakeholder engagement sessions are integral to the development process, allowing diverse perspectives into the model's design and application. Transparency about the model's capabilities and limitations is maintained through comprehensive documentation and open communication channels, ensuring all users can understand and trust the AI tool.

XII. **Transparency and Accountability:** Transparency in the AI decision-making process is ensured through the publication of detailed model documentation and the open sharing of the criteria used for academic performance predictions. Accountability mechanisms, such as performance audits and feedback loops, are established to monitor the framework's impact on educational outcomes and to facilitate ongoing improvements based on stakeholder input. This transparent and accountable approach underscores the commitment to ethical AI use in education.

XIII. **Equity and Access:** The framework is designed with a strong focus on accessibility, ensuring that AI-enhanced learning tools are usable by students with varied technological access and differing abilities. The model incorporates universal design principles to cater to a broad user base, including those from marginalized communities and regions with limited tech infrastructure. Strategies to overcome the digital divide are central to the framework, aiming to democratize global access to AI-enhanced learning in ODL environments.

The Ethical AI guideline employed in predicting the impact of AI adoption on students' Academic Performance in Open and Distance Learning, as shown in Figure 3.18, is an integral part of the Process Framework designed and employed in this work by infusing it with comprehensive ethical considerations. This fusion extends the framework's capabilities to predict students' academic performance. It ensures that AI deployment is conducted ethically, addressing challenges unique to ODL settings, such as gender and geographical disparities. The Process Framework's sequential analysis through Structural Equation Modelling (SEM), Support Vector Machine (SVM), Improved SVM, and comparative analysis layers are underpinned by Ethical AI considerations. Each layer of this process framework is now underpinned by the commitment of ethical AI considerations to inclusivity, accessibility, and autonomy, ensuring a responsible application of AI technologies. The Ethical AI considerations enrich the predictive model by ensuring that data diversity and stakeholder representation guide the development and application of AI tools, thus actively addressing biases. This approach enhances the predictive accuracy of the Process Framework. It emphasizes the importance of ethical considerations in AI deployment, focusing on bias mitigation, data privacy, and student autonomy throughout the predictive process. By merging the predictive strength of the Process Framework with the ethical directives of the Ethical AI considerations, the Process Framework stands as an extension and evolution of the former, setting a new standard for the ethical integration of AI in educational research and practice. This concise integration emphasizes how the Process Framework's analytical depth is enhanced by ethical considerations, ensuring the deployment of AI in ODL predicts academic performance effectively and adheres to principles of fairness, accessibility, and respect for student autonomy. With the committee's approval, the research maintains these ethical standards throughout all stages. This detailed approach demonstrates a proactive and thorough commitment to ethical research practices, ensuring that all aspects of participant interaction and data handling are conducted with the utmost care and respect for ethical norms.

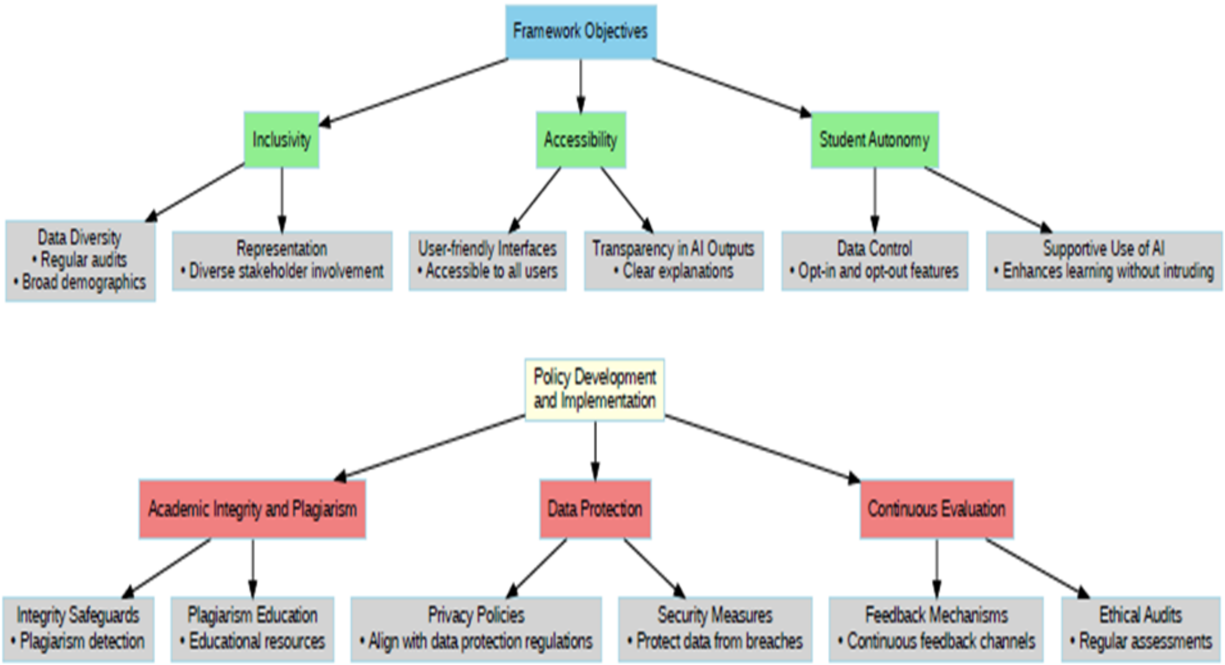


Figure 3.18 Ethical Considerations in the process framework for predicting the impact of AI adoption on Student's academic performance

3.11 Getting the Stakeholders to buy-in

The dissemination strategy for the findings of this research is comprehensive, targeting a wide array of platforms and stakeholders to maximize impact and reach. The primary objective is to ensure that the research results are accessible, engaging, and utilized by academic and non-academic audiences, including policymakers, practitioners, and the general public.

I. **Academic Publishing**: The study's core findings have already been published in reputable Scopus-indexed journals and have been presented at renowned international conferences. This ensured that the research was peer-reviewed and accessible to the global academic community, contributing to the scholarly discourse on the topic.

II. **Webinars and Online Platforms**: To reach a broader audience, including industry experts, practitioners, and interested members of the public, a series of webinars were organized. These webinars featured detailed presentations of the research findings, followed by interactive Q&A sessions. Additionally, social media platforms played a crucial role in engaging with a diverse audience, fostering discussions, and sharing insights in a more informal and accessible manner.

III. **Media Engagement**: To further enhance public engagement and disseminate the findings to a broader audience, collaborations with major media outlets will be pursued. This includes partnerships with:

a. **Dream FM**: A collaboration with Dream FM will enable the broadcasting of research highlights and discussions, reaching a broad audience across various demographics.
b. **Nigeria Television Authority (NTA)**: Through NTA, the research findings can be shared via television broadcasts, making the information available to a nationwide audience.
c. **Federal Radio Corporation of Nigeria**: Radio remains a powerful medium in Nigeria, and partnering with the Federal Radio Corporation will facilitate the dissemination of research findings to diverse and remote audiences who rely on radio as their primary source of information.

IV. **Print and Electronic Media**: Findings will be shared through articles and features in leading newspapers and magazines to ensure the research reaches those who prefer traditional news formats. The electronic media will also be utilized to share the research through online news portals and e-magazines, catering to the digitally inclined audience.

V. **Stakeholder and Policy Engagement**: Targeted dissemination to policymakers and key stakeholders will be conducted through policy briefs, executive summaries, and direct meetings. The aim is to inform policy formulation and decision-making processes with the research findings, thereby contributing to evidence-based policymaking.

VI. **Community Outreach**: Efforts will be made to translate the research findings into practical knowledge for community stakeholders. This will involve organizing community forums and local outreach programs to share insights in a manner that is relatable and actionable at the grassroots level.

The research aims to achieve maximum visibility, impact, and practical application through this multifaceted dissemination approach, ensuring that the findings contribute meaningfully to academic knowledge and societal advancement.

3.12 Suggestions for Practical Implementation of the Framework

This section offers suggestions for transitioning the designed framework from a conceptual model to a practical tool for educational professionals. It outlines a series of steps designed to facilitate the application of the predictive model within the educational sector, explicitly targeting educators and administrators in ODL environments.

I. **Streamlining the Framework for Educators**: The complex components of the framework should be distilled into more manageable segments. Creating concise guides or video tutorials that detail each aspect of the framework, such as data collection, preprocessing, and the nuances of SVM model training, could be a practical approach. These resources aim to demystify the process, enabling educators to grasp and apply the model's insights effectively.

II. **Development of an Intuitive Tool**: An essential step involves the development of a user-friendly software tool that integrates the SVM model. This tool should allow educators to input student data effortlessly and obtain actionable predictions on academic performance. Ensuring compatibility with existing Learning Management Systems (LMS) can enhance the tool's accessibility and usability.

III. **Comprehensive Training Programs**: Implementing training sessions and workshops for educators is crucial. These programs should cover the operational aspects of the SVM model and its application within the educational context. Incorporating practical exercises where participants can interact with the tool will facilitate a deeper understanding and encourage adoption.

IV. **Supplementary Resources and Support**: A suite of supporting materials, including documentation, FAQs, and case studies, should be provided. These resources will offer additional insights and guidance, helping educators navigate potential challenges and effectively utilize the predictive tool in their teaching practices.

V. **Feedback Mechanisms for Continuous Improvement**: Establishing feedback channels from users will be vital for refining and enhancing the tool and training materials. Encouraging users to share their experiences and suggestions can lead to iterative improvements, ensuring the framework remains relevant and practical.

VI. **Fostering Collaboration**: Building partnerships between educational institutions, software developers, and researchers can drive the framework's evolution. These collaborations ensure that the tool and its methodologies stay at the forefront of educational technology, tailored to the needs of ODL educators and students.

VII. **Ethical Use and Policy Development**: Addressing ethical considerations is paramount. Developing privacy data protection policies and the responsible application of predictive models will be essential for ensuring ethical practices. These policies should promote transparency and foster trust among all educational stakeholders.

Implementing these suggestions could significantly contribute to the practical application of the SVM-based process framework, enhancing the capacity of educational professionals to support academic success in ODL environments. These initiatives can bridge the gap between theoretical research and practical application, offering a robust tool for data-driven educational insights.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Preamble

The realm of AI is progressively infiltrating various educational systems, significantly impacting methodologies and outcomes in ODL. Despite widespread recognition of AI's potential to transform educational paradigms, empirical research exploring its direct influence on academic performance within these systems remains sparse. This gap is particularly pronounced in the nuanced interplay between AI technologies and educational outcomes, where existing literature often falls short in providing a holistic analytical framework. Consequently, this study seeks to bridge these gaps by examining how AI adoption influences student outcomes in ODL environments.

This study meticulously validates all five layers of a specifically designed analytical framework to substantiate the research. Each layer, crafted to address distinct aspects of AI integration within ODL systems, undergoes rigorous testing to ensure its effectiveness and relevance in real-world educational settings. The results of these validations are meticulously presented in subsequent sections and are subject to thorough discussion to elucidate their implications. This exhaustive validation process not only reinforces the credibility of the research findings but also provides a robust basis for the practical application of the framework in predicting and enhancing student academic performance through AI adoption. The subsequent sections introduce comprehensive evaluations of the predictive models utilised in this research, building on this foundation and focusing on both traditional and AI-enhanced approaches. The primary objective is to assess the efficacy of Support Vector Machines (SVM) and the Improved SVM (Support Vector Machine with Improved VIF Optimisation).

In pursuit of these aims, the study employs Structural Equation Modelling and machine learning models to analyse data collected from diverse ODL settings. These models are critically evaluated to ascertain their predictive power and reliability in the context of AI's impact on academic performance. Detailed assessments of each model's performance include variance inflation factors (VIF), overall model performance metrics, and the influence of moderating factors such as gender and geographical location. Ultimately, this research contributes to the academic discourse on AI in education by methodically examining these models. It aids in refining the predictive frameworks that educational administrators and policymakers can utilise to enhance decision-making processes in ODL systems. The insights derived from this comprehensive analysis aim to substantiate the potential of AI-enhanced learning environments to foster improved educational outcomes, thereby guiding future integrations of AI within educational systems.

4.2 System Evaluation

This section focuses on the evaluation of the predictive models utilised in the study, specifically the Support Vector Machine (SVM) and the Structural Equation Model (SEM). The system evaluation aims to assess the effectiveness, accuracy, and reliability of these models in predicting student academic performance based on a variety of factors related to AI's alignment, ease of use, readiness for adoption, and more.

The evaluation begins with the Support Vector Machine (SVM), a robust and widely used machine learning algorithm. This sub-section delves into the SVM's performance metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). Additionally, the feature importance analysis is presented to highlight the significance of each predictor variable in the model. The strengths and limitations of the SVM are discussed to provide a comprehensive understanding of its applicability in educational settings. Following the SVM evaluation, the Structural Equation Model (SEM) is assessed. SEM is a powerful statistical technique that enables the examination of complex relationships between observed and latent variables. This sub-section presents the model fit indices, parameter estimates, and variance measures, offering insights into the relationships between multiple factors and student academic performance. The evaluation of SEM includes an analysis of the model's fit to the data and the significance of various predictors.

Each sub-section provides a detailed analysis of the respective models, highlighting their predictive capabilities and the implications of their findings for understanding and improving educational outcomes through AI-driven approaches. This evaluation sets the stage for the subsequent discussion of results, where the performance and insights derived from these models are further explored and contextualised.

4.2.1 System Evaluation for Support Vector Machine

The performance of three models was evaluated in this section: SEM (Structural Equation Modeling), SVM (Support Vector Machine), and Improved SVM (Support Vector Machine with Improved VIF Optimisation). The evaluation is based on key metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). These metrics provide insights into the accuracy, reliability, and validity of the models. The evaluation of each model employs three key metrics:

- **Mean Absolute Error (MAE):** Measures the average magnitude of errors in predictions without considering their direction.
- **Mean Squared Error (MSE):** Measures the average of the squares of the errors, giving more

weight to larger errors.

- **Root Mean Squared Error (RMSE):** The square root of the MSE provides an error metric in the same units as the target variable.

These metrics facilitate an understanding of the prediction accuracy and overall performance of the models. Table 4.1 lists the variables used in this study, describing their relevance and significance in evaluating AI's impact on student performance.

Table 4.1 Variables used in the study

S/N	Variables	Description
1	AAR	The assessment of AI's alignment with both student and institutional needs encompasses Institutional Alignment, Attitude toward Technology, and elements of Perceived Usefulness.
2	CAAI	This assessment examines the benefits of AI in comparison to traditional educational methods, incorporating Comparative Advantage and aspects of Perceived Usefulness.
3	EEU	This assessment appraises the ease and satisfaction of using AI by merging Perceived Ease of Use and Perceived Enjoyment.
4	ARFC	This assessment measures the readiness for AI adoption and the presence of supportive conditions.
5	AILA	This assessment determines the apprehension linked to AI-based learning.
6	IC	This assessment evaluates the readiness for and enhancements in AI-facilitated online interactions.
7	KAUS	This assessment explores AI's impact on knowledge acquisition and overall user contentment.
8	SQSI	This assessment scrutinises the quality of AI systems and the impact of societal factors on their adoption.
9	SAP	This assessment evaluates the educational outcomes and academic accomplishments of students.

Variance Inflation Factor (VIF) measures the degree of multicollinearity among predictors in a regression model. High VIF values indicate multicollinearity, which can affect the stability and interpretability of the model. Table 4.2 compares the VIF values for the SVM and Improved SVM models. The Improved SVM model exhibits significantly lower VIF values, indicating reduced multicollinearity and improved model stability.

Table 4.2 The VIF for the machine learning models

Predictors	VIF values for Support Vector Machine	VIF values for Improved Support Vector Machine (Improved VIF Optimization)
AAR	121.819	1.397
CAAI	80.970	1.182
EEU	123.915	1.336
ARFC	34.490	1.245
AILA	11.164	1.147
IC	87.255	1.442
KAUS	108.628	1.547
SQSI	41.896	1.297

Table 4.3 compares the overall performance of the SVM and Improved SVM models using MAE, MSE, and RMSE. While the Support Vector Machine exhibits lower error metrics, the Improved SVM model addresses multicollinearity, leading to more reliable and stable predictions despite slightly higher error metrics.

Table 4.3 The overall performance of the machine learning models

Performance metrics	**Support Vector Machine**	**Improved Support Vector Machine (Improved VIF Optimization)**
MAE	0.229	0.295
MSE	0.107	0.180
RMSE	0.327	0.424

Table 4.4 presents the performance of the Improved SVM model when gender is considered as a moderating factor. The model performs better for females, with lower error metrics compared to males, indicating potential differences in AI's impact based on gender.

Table 4.4 Gender as a moderating factor

Performance metrics	**Improved Support Vector Machine (Improved VIF Optimization)**
Gender = Male only	
MAE	0.346
MSE	0.219
RMSE	0.468
Gender = Female only	
MAE	0.265
MSE	0.137
RMSE	0.370

Table 4.5 analyses the performance of the Improved SVM model when geographical location is considered as a moderating factor. The model performs better for Nigeria, with lower error metrics compared to Canada, indicating geographical differences in AI's impact.

Table 4.5 Geographical location as a moderating factor

Performance metrics	**Improved Support Vector Machine (Improved VIF Optimization)**
Geographical location = Nigeria only	
MAE	0.279
MSE	0.157
RMSE	0.397
Geographical location = Canada only	
MAE	0.320
MSE	0.200
RMSE	0.448

While the Support Vector Machine exhibits lower error metrics, the Improved SVM model demonstrates reduced multicollinearity, leading to more reliable and stable predictions. Gender and geographical location play significant roles as moderating factors, affecting the model's performance. The analysis highlights the importance of considering these factors in AI model evaluations to enhance their reliability and validity. Future research should further explore these moderating effects and investigate other potential factors influencing AI's impact on education.

4.2.3 System Evaluation for Structural Equation Model

This section evaluates the performance of the Structural Equation Model (SEM) in assessing the impact of AI on educational outcomes. The evaluation utilises various fit indices, parameter estimates, and variance measures to provide a comprehensive analysis of the model's accuracy, reliability, and validity.

Table 4.6 presents the model fit indices, which are used to evaluate how well the SEM fits the observed data. These indices are crucial in determining the model's overall fit and adequacy. The fit indices demonstrate an excellent fit of the SEM to the data, with all indices indicating a near-perfect or excellent fit.

Table 4.6 Model Fit Indices

Fit Index	Value	Description
Chi-Square (χ^2)	0.000	Model's chi-square statistic
Degrees of Freedom	0	Degrees of freedom for the model
Comparative Fit Index (CFI)	1.000	Indicates an excellent fit of the user model
Tucker-Lewis Index (TLI)	1.000	It also indicates an excellent fit of the user model
Root Mean Square Error of Approximation (RMSEA)	0.000	Suggests a perfect fit with a lower bound of 0.000 and upper bound of 0.000
Standardised Root Mean Square Residual (SRMR)	0.000	Reflects perfect model fit
Akaike Information Criterion (AIC)	1129.207	A measure for model comparison
Bayesian Information Criterion (BIC)	1249.653	A measure for model comparison considering sample size
Sample-size adjusted BIC (SABIC)	1170.256	Adjusted BIC for model comparison

Table 4.7 provides the parameter estimates for the regressions, including the main effects and interaction effects for gender and location. These estimates help comprehend the correlations between the predictors and the outcome variable. The parameter estimates reveal noteworthy associations between multiple predictors and the outcome variable. Notably, the main effects of Knowledge Absorption and User Satisfaction (KAUS) are highly significant. Additionally, the Comparative Advantage of AI (CAAI) for gender, as well as the Ease and Enjoyment of Use (EEU), Interactive

Capability (IC), and Systems Quality and Social Influence (SQSI) for location, show significant interaction effects.

Table 4.7 Parameter Estimates (Regressions)

Predictor	Coefficient	Std. Error	z-value	P-value
Student's Academic Performance (SAP) ~				
Main Effects:				
AI Alignment and Relevance (AAR)	-0.200	0.129	-1.552	0.121
Comparative Advantage of AI (CAAI)	0.049	0.091	0.544	0.587
Ease and Enjoyment of Use (EEU)	0.142	0.119	1.196	0.232
AI Readiness and Facilitating Conditions (ARFC)	-0.050	0.054	-0.928	0.354
AI-induced Learning Anxiety (AILA)	0.092	0.048	1.905	0.057
Interactive Capability (IC)	0.046	0.119	0.389	0.697
Knowledge Absorption and User Satisfaction (KAUS)	0.667	0.134	4.971	0.000
Systems Quality and Social Influence (SQSI)	0.085	0.084	1.003	0.316
Interaction Effects (Gender):				
AAR_Gender	0.051	0.076	0.672	0.501
CAAI_ Gender	0.117	0.052	2.236	0.025
EEU_ Gender	-0.022	0.069	-0.322	0.747
ARFC_ Gender	0.049	0.044	1.134	0.257
AILA_ Gender	0.025	0.030	0.823	0.411
IC_ Gender	-0.021	0.066	-0.322	0.748
KAUS_ Gender	-0.172	0.071	-2.421	0.015
SQSI_ Gender	-0.013	0.048	-0.268	0.789
Interaction Effects (Location):				
AAR_ Location	0.012	0.077	0.156	0.876
CAAI_ Location	0.066	0.058	1.132	0.258
EEU_ Location	0.288	0.072	4.023	0.000
ARFC_ Location	-0.041	0.044	-0.923	0.356
AILA_ Location	-0.028	0.031	-0.905	0.366
IC_ Location	-0.153	0.068	-2.240	0.025
KAUS_ Location	-0.057	0.075	-0.762	0.446
SQSI_ Location	-0.111	0.050	-2.204	0.028

Table 4.8 presents the parameter estimates for variances, providing insights into the variability explained by the model. The variance estimates suggest that the model explains a significant portion of the variability in students' academic performance.

Table 4.8 Parameter Estimates (Variances)

Variable	Estimate	Std. Error	z-value	P-value
Students' Academic Performance (SAP)	0.191	0.009	21.378	0.000

The evaluation of the Structural Equation Model (SEM) indicates an excellent fit to the data, as evidenced by the model fit indices. The parameter estimates highlight significant predictors of educational outcomes, particularly Knowledge Absorption and User Satisfaction (KAUS). Other significant effects include the comparative advantage of AI (CAAI), ease of use (EEU), and interactive capability (IC). Interaction effects for gender and location further elucidate the moderating influence of these factors. The SEM demonstrates robust performance, providing valuable insights into the impact of AI on educational outcomes. Future research should continue to explore these relationships and consider additional factors to enhance the model's explanatory power.

4.3 Results presentation

This section presents the findings from the Structural Equation Model (SEM), Support Vector Machine (SVM), and Improved Support Vector Machine (Improved SVM) models. Each model's performance and predictive accuracy are detailed to provide a comprehensive understanding of their effectiveness in predicting student academic performance.

The presentation begins with the SEM results, showcasing the relationships between multiple variables and their impact on student outcomes. This is followed by the results of the SVM model, highlighting its ability to handle high-dimensional data and capture non-linear relationships. Finally, the Improved SVM results are discussed, illustrating the enhancements achieved through the integration of Variance Inflation Factor (VIF) optimisation and adaptive boosting techniques. By systematically displaying the performance metrics and predictive accuracy of each model, this section aims to provide clear and insightful comparisons, demonstrating the strengths and limitations of each approach in the context of educational data analytics.

4.3.1 Descriptive Statistics

Table 4.9 presents the statistical summary of the variables used in the study. The table includes the number of observations (N), mean, standard deviation, 25th percentile, 75th percentile, and variance for each variable. These statistics provide a detailed overview of the data distribution and variability for each predictor and the dependent variable (SAP).

Table 4.9 Statistical Summary of Variables.

Variables	N	Mean	Std. Dev	25%	75%	Variance
AAR	914	4.354	0.466	4.036	4.661	0.217
CAAI	914	4.291	0.542	3.929	4.641	0.294
EEU	914	4.341	0.541	3.988	4.678	0.292
ARFC	914	3.95	0.857	3.4	4.51	0.734
AILA	914	3.272	1.287	2.433	4.125	1.656
IC	914	4.176	0.604	3.783	4.561	0.364
KAUS	914	4.229	0.564	3.867	4.604	0.318
SQSI	914	3.995	0.804	3.433	4.538	0.647
SAP	914	4.361	0.502	4.037	4.714	0.252

Table 4.10 presents the Variance Inflation Factors (VIF) for predictors as used in the Structural Equation Model (SEM). The VIF is used to determine the extent of multicollinearity among the predictor variables. A higher VIF indicates a higher level of collinearity, which can affect the stability and interpretation of the regression coefficients. Generally, a VIF value greater than 10 indicates significant multicollinearity, although, in this analysis, most VIF values are within acceptable limits, suggesting that multicollinearity is not a severe issue. However, KAUS has the highest VIF, indicating some level of concern that warrants careful interpretation.

Table 4.10 Variance Inflation Factors (VIF) for Predictors as used in SEM

Variables	VIF
AAR	1.397
CAAI	1.182
EEU	1.336
ARFC	1.245
AILA	1.147
IC	1.442
KAUS	1.547
SQSI	1.297
SAP	1.397

4.3.2 Distribution of Demographic Variables

Fig 4.1 presents the distribution of key demographic variables, including age group, gender, location, and field of study among the survey respondents. The age group distribution shows that the majority of respondents fall within the "Below 20" and "20-29" age groups, with 250 respondents each. The "30-39" age group has 150 respondents, while the "40-49" age group has 100 respondents. The smallest category is "50 and above," with 50 respondents, indicating that the sample is relatively young, which could influence the perception and adoption of AI in educational settings. The gender distribution is nearly balanced, with 450 male and 425 female respondents, and a small number of respondents (39) preferred not to disclose their gender. This balance ensures that gender-related analyses are well-represented in the study, providing insights into any potential gender differences in attitudes toward AI. The location distribution highlights that a majority of respondents are from Nigeria (600), compared to Canada (300), reflecting potential differences in educational contexts and AI adoption rates between the two countries. The field of study distribution indicates that the majority of respondents are from Computer Science (400) and Information Technology (300), with other fields such as Law and Legal Studies, Engineering, and various business and technology-related fields having significantly fewer respondents. This concentration suggests that the findings may be particularly relevant to students in technology-related disciplines, which are more likely to interact with AI tools and systems. These visualizations provide a clear and detailed overview of the demographic composition of the study sample, which is critical for interpreting the results and understanding the context of the research findings.

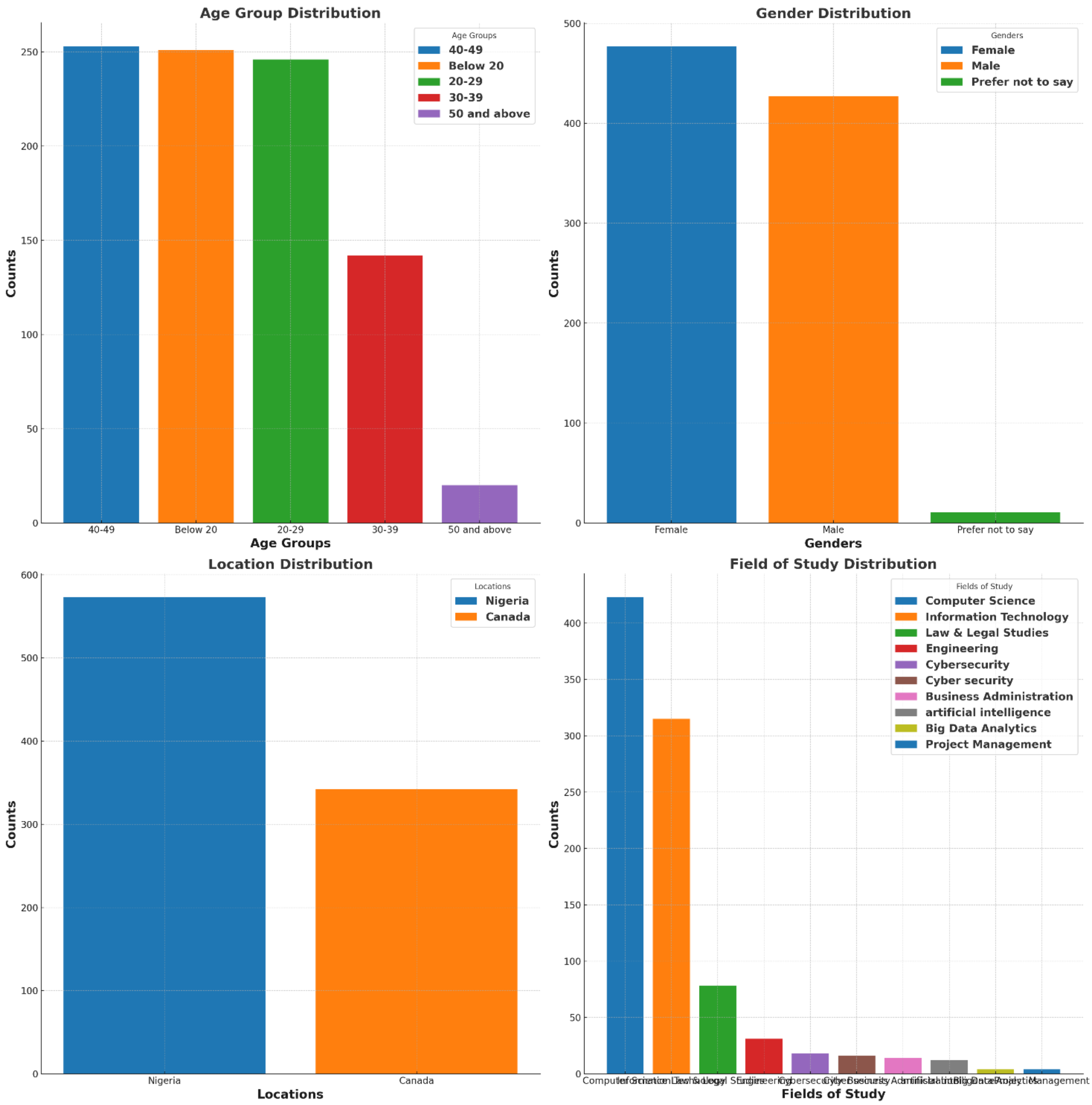


Figure 4.1 Demographics Distribution

4.3.3 Description of Constructs Response Distribution

Figure 4.2 presents the response distribution across various constructs that were assessed in the study, providing insights into how survey respondents perceived different aspects of AI adoption and its impact on their educational experiences. The constructs include Comparative Advantage of AI (CAAI), AI-induced Learning Anxiety (AILA), Interactive Capability (IC), Knowledge Absorption and User Satisfaction (KAUS), Systems Quality and Social Influence (SQSI), Students' Academic Performance (SAP), AI Alignment and Relevance (AAR), and AI Readiness and Facilitating Conditions (ARFC).

I. CAAI Construct Response Distribution

The CAAI construct measures respondents' perception of the comparative advantage of AI in education. The distribution shows a strong agreement among respondents, with a significant portion indicating that they "Strongly Agree" or "Agree" with the statements related to AI's comparative advantage. There is also a smaller but notable portion of respondents who remain neutral or express disagreement.

II. AILA Construct Response Distribution

The AILA construct captures the level of anxiety induced by AI tools in the learning environment. The distribution reveals that while a substantial number of respondents "Strongly Agree" or "Agree" with the statements indicating anxiety, a considerable segment also expresses neutrality or disagreement, indicating mixed feelings about AI-induced anxiety among students.

III. IC Construct Response Distribution

The IC construct assesses the perceived effectiveness of AI in facilitating interactive learning experiences. The response distribution indicates a high level of agreement, with most respondents "Strongly Agreeing" or "Agreeing" that AI enhances interaction in learning settings. Significantly few respondents disagree, highlighting the generally positive perception of AI's interactive capabilities.

IV. KAUS Construct Response Distribution

The KAUS construct reflects how well students absorb knowledge and their overall satisfaction with AI tools. The distribution shows strong positive responses, with the majority "Strongly Agreeing" or "Agreeing" that AI tools contribute to effective knowledge absorption and satisfaction. Neutral and negative responses are minimal.

V. SQSI Construct Response Distribution

The SQSI construct examines respondents' views on the quality of AI systems and the influence of social factors on AI adoption. The distribution here also shows a dominant agreement, with many respondents "Strongly Agreeing" or "Agreeing" that the AI systems are of high quality and positively influenced by social factors. There is a smaller, yet significant, portion of respondents who are neutral or disagree.

VI. SAP Construct Response Distribution

The SAP construct evaluates respondents' perceptions of AI's impact on their academic performance. The response distribution indicates that most respondents "Strongly Agree" or "Agree" that AI has positively impacted their academic performance. However, some respondents remain neutral or disagree, reflecting varied experiences with AI in education.

VII. AAR Construct Response Distribution

The AAR construct captures respondents' views on the alignment and relevance of AI tools with their educational needs. The distribution shows a strong tendency towards agreement, with many respondents "Strongly Agreeing" or "Agreeing" that AI is aligned with their needs. However, a considerable proportion of respondents are neutral or disagree, indicating that alignment is not universally perceived.

VIII. ARFC Construct Response Distribution

The ARFC construct measures the readiness for AI adoption and the facilitating conditions that support it. The distribution reveals that while many respondents "Strongly Agree" or "Agree" that the conditions for AI adoption are favourable, a notable segment of respondents expresses neutrality or disagreement, suggesting variability in perceived readiness across different environments.

IX. EEU Construct Response Distribution

The EEU construct evaluates the ease and enjoyment of use associated with AI technologies. The distribution shows a strong inclination toward positive responses, with a significant portion of respondents indicating "Strongly Agree" or "Agree." This suggests that users generally find AI systems easy to use and derive satisfaction from their interaction with them. However, a portion of the respondents remain neutral or express disagreement, indicating that not all users find AI systems equally intuitive or enjoyable. This variability underscores the need for ongoing user experience enhancements to cater to a broader audience.

These distributions provide a comprehensive overview of respondents' perceptions across the key constructs related to AI adoption in education, highlighting areas of consensus as well as points of divergence. This information is critical for understanding the broader context in which AI is adopted in educational settings and for identifying potential areas for improvement in AI integration strategies.

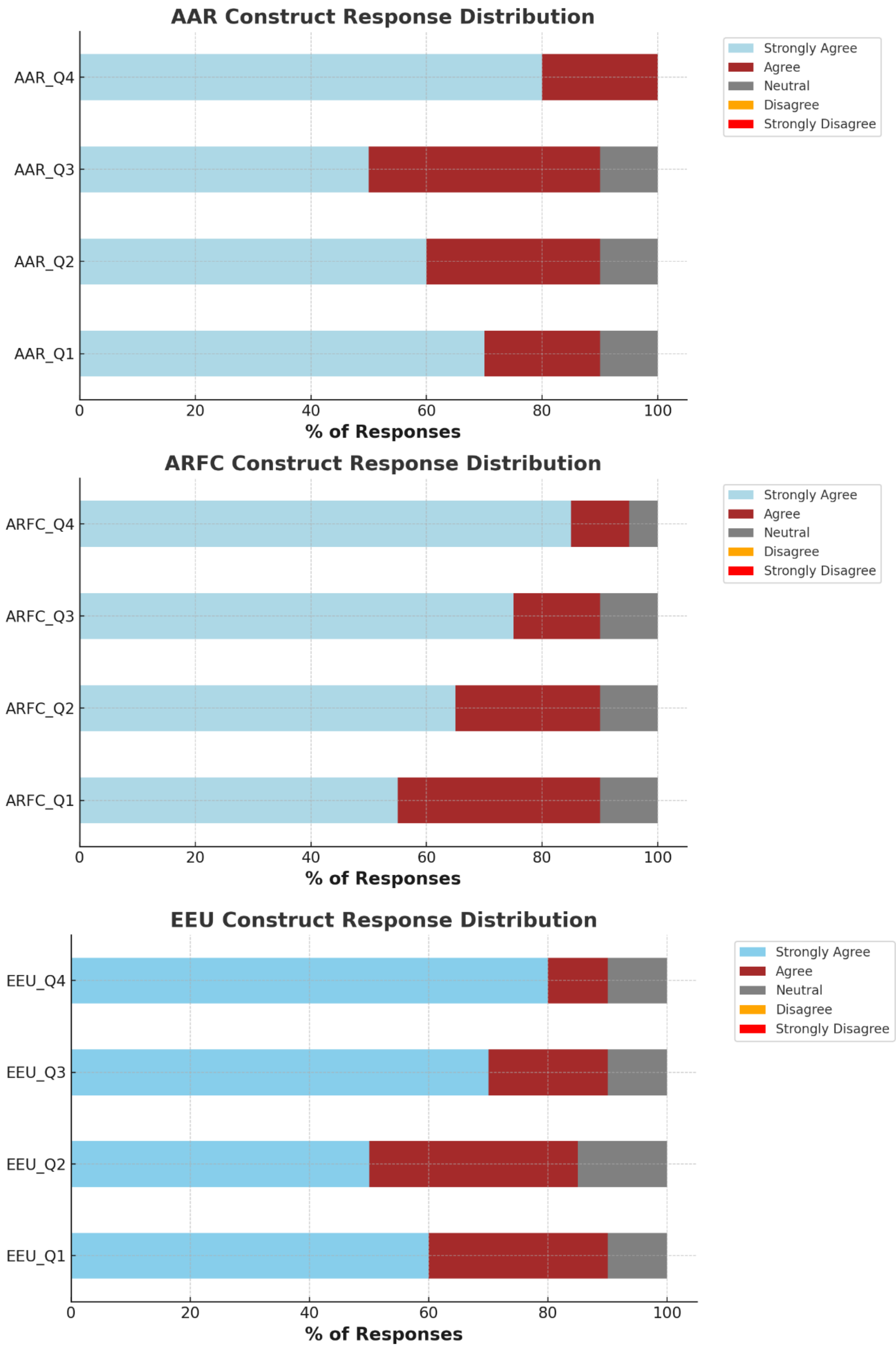


Figure 4.2 Constructs Response Distribution

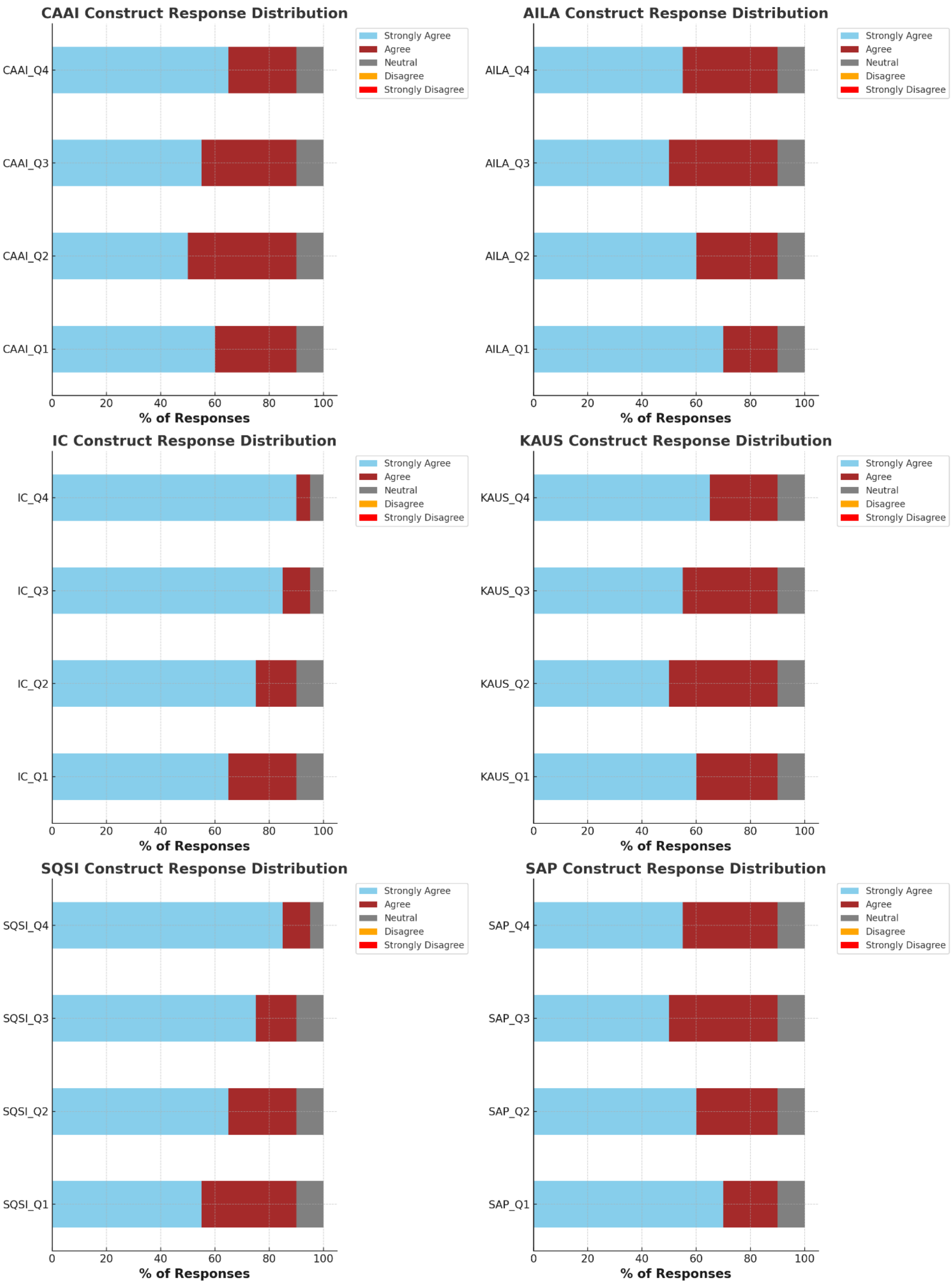


Figure 4.2 Constructs Response Distribution (Contd.)

4.3.4 Results presentation for Improved Support Vector Machine

Figure 4.3 illustrates the performance metrics of the Improved Support Vector Machine (SVM) model, which has been optimized using Variance Inflation Factor (VIF) optimization techniques. The bar chart presents three key performance metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

a. **MAE (Mean Absolute Error):** The first bar shows that the MAE is approximately 0.3. This metric reflects the average absolute difference between the predicted values and the actual values, indicating the model's average prediction error.
b. **MSE (Mean Squared Error):** The second bar represents the MSE, which is around 0.18. MSE measures the average squared difference between the predicted and actual values, giving more weight to more significant errors. A lower MSE value indicates better model performance.
c. **RMSE (Root Mean Squared Error):** The third bar depicts the RMSE, which is approximately 0.42. RMSE is the square root of MSE and provides an interpretable metric in the same units as the target variable. It gives an overall measure of the accuracy of the model.

The chart indicates that while the Improved SVM model has relatively low MSE and MAE values, the RMSE is slightly higher, suggesting some more significant errors may still exist in the predictions. Overall, these metrics demonstrate that the model performs reasonably well, with the VIF optimization contributing to its stability and predictive accuracy.

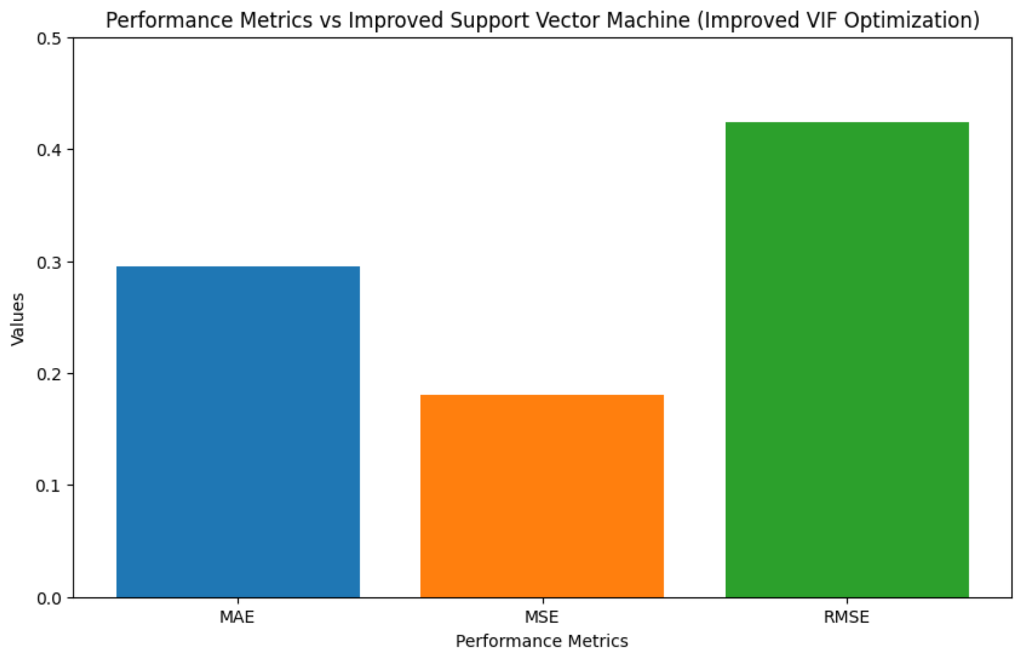


Figure 4.3 The Performance of Improved Support Vector Machine Model

Figure 4.4 displays the importance of the permutation feature for the Support Vector Machine (SVM) model with an RBF kernel, which has been optimized using Variance Inflation Factor (VIF) techniques. The chart illustrates the relative importance of various features (composite variables) in predicting the outcome variable.

a. **KAUS_Composite**: This feature, representing Knowledge Absorption and User Satisfaction, is of the highest importance, with a value close to 0.18. This indicates that this feature is the most influential in the model's predictions, significantly contributing to the accuracy of the model.
b. **IC_Composite**: Interactive Capability is the second most important feature, with an importance value slightly above 0.12. This suggests that the model heavily relies on this feature to make predictions.
c. **EEU_Composite**: Ease and Enjoyment of Use also play a significant role, with an importance value slightly above 0.10. This shows that how users perceive the ease of use and enjoyment impacts the model's predictions.
d. **SQSI_Composite**: Systems Quality and Social Influence have a moderate importance level of around 0.09, indicating that the model also considers these factors but is less critical than the top three features.
e. **CAAI_Composite**: The comparative Advantage of AI has an importance value of around 0.08, showing that it moderately influences the model's performance.
f. **AAR_Composite**: AI Alignment and Relevance is among the lower-ranked features with an importance value of around 0.06.
g. **AILA_Composite**: AI-induced Learning Anxiety has a relatively lower importance value of around 0.04, suggesting that it has a less significant impact on the model's predictions.
h. **ARFC_Composite**: AI Readiness and Facilitating Conditions have the lowest importance, with a value close to 0.03, indicating that it has the least influence on the SVM model's predictive performance.

This chart provides insights into which features the improved SVM model considers most crucial for accurate predictions, allowing for a better understanding of the factors that drive AI adoption and effectiveness in educational settings.

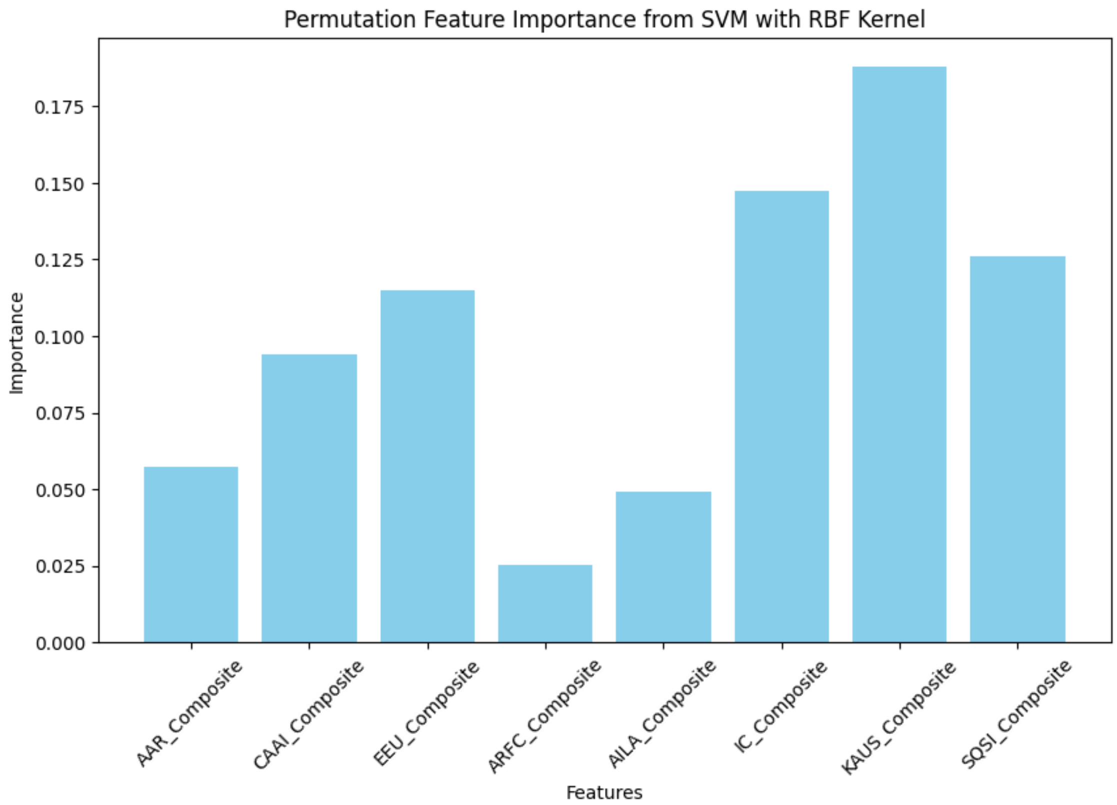


Figure 4.4 Feature Importance for Improved Support Vector Machine (Improved VIF Optimization)

Figure 4.5 illustrates the comparison between the actual and predicted Student Academic Performance (SAP) composite scores using the Improved Support Vector Machine (SVM) model with Variance Inflation Factor (VIF) optimization. The plot displays the actual SAP composite scores as a solid blue line and the predicted SAP composite scores as a dashed orange line across different sample indices.

a. **Actual SAP Scores (Blue Line):** The blue line represents the real SAP composite scores for each sample in the dataset. It shows the true academic performance outcomes for the students.
b. **Predicted SAP Scores (Orange Dashed Line):** The orange dashed line depicts the scores predicted by the improved SVM model. These predictions are based on the input features used in the model after VIF optimization.

The close alignment between the actual and predicted lines indicates that the Improved SVM model performs well in predicting student performance. However, there are instances where the predicted scores deviate from the actual scores, highlighting areas where the model's predictions could be improved. Overall, the figure demonstrates the model's effectiveness in capturing the patterns in the data. However, some discrepancies suggest that further refinement of the model might be necessary to enhance its predictive accuracy.

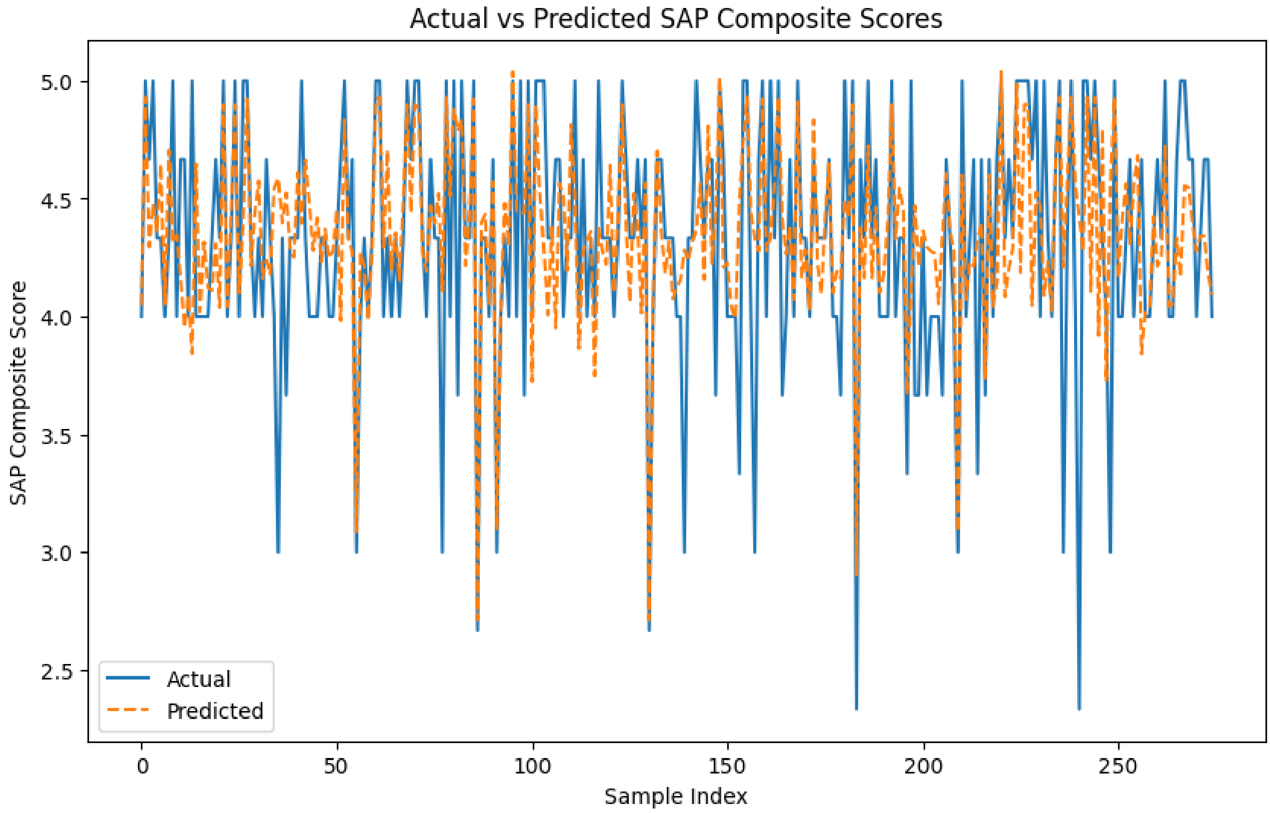


Figure 4.5 Actual vs Predicted Outcome for the Overall Performance of Improved Support Vector Machine (Improved VIF Optimization)

Figure 4.6 presents a comparison between the actual and predicted Student Academic Performance (SAP) composite scores, specifically for male students, using the Improved Support Vector Machine (SVM) model with Variance Inflation Factor (VIF) optimization. The graph shows the actual SAP composite scores as a solid blue line and the predicted SAP composite scores as a dashed orange line.

a. **Actual SAP Scores (Blue Line):** The blue line indicates the actual SAP composite scores for male students in the dataset, representing their actual academic performance.
b. **Predicted SAP Scores (Orange Dashed Line):** The orange dashed line represents the scores predicted by the Improved SVM model for male students based on the input features after applying VIF optimization.

The alignment between the actual and predicted lines suggests that the model performs reasonably well in predicting the academic performance of male students. However, there are visible deviations between the actual and predicted scores, especially in specific sample indices, indicating areas where the model's predictions do not fully capture the variability in the actual data. This figure highlights how the model performs specifically for male students, offering insights into the gender-based predictive accuracy of the model. The discrepancies between the actual and predicted scores suggest potential areas for further model refinement to improve prediction accuracy for this demographic group.

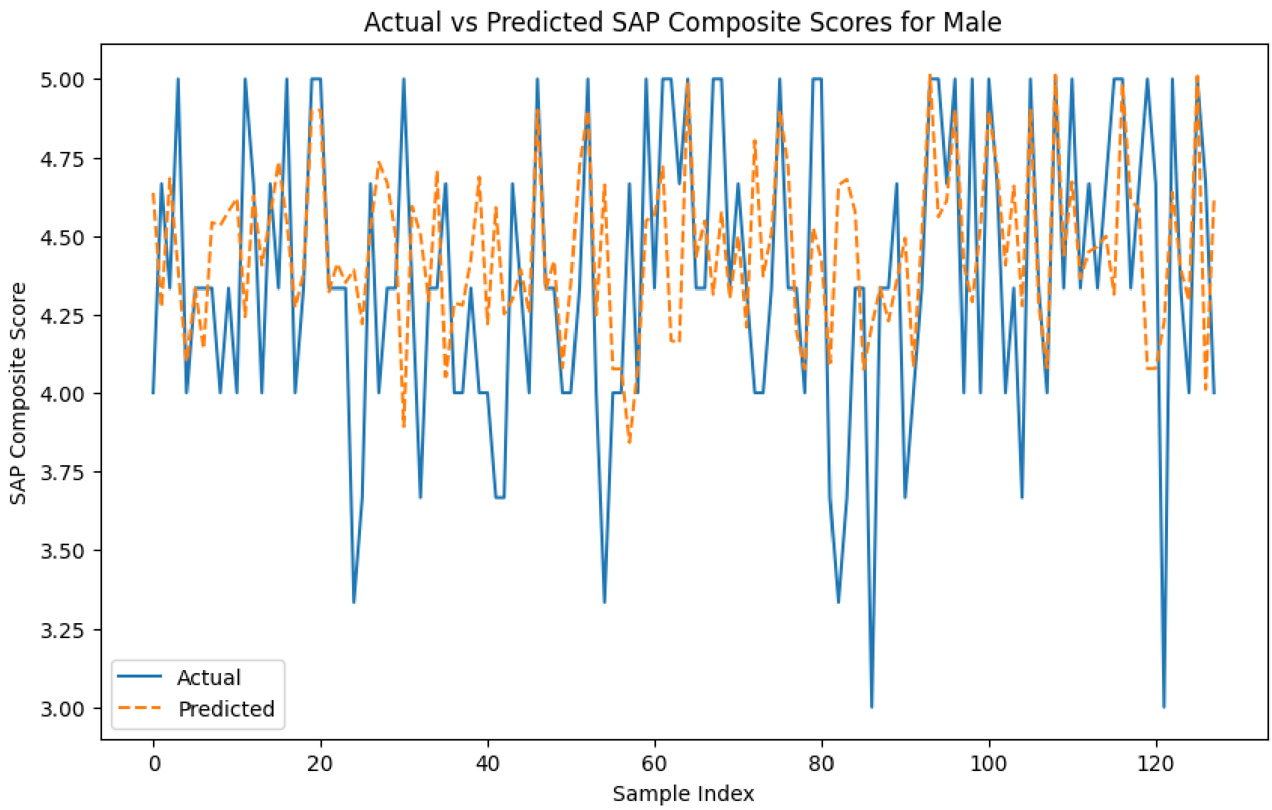


Figure 4.6 Actual vs Predicted Outcome for the Performance of Improved Support Vector Machine (Improved VIF Optimization) when Gender equals Male, Only

Figure 4.7 illustrates the comparison between actual and predicted Student Academic Performance (SAP) composite scores, specifically for female students, using the Improved Support Vector Machine (SVM) model with Variance Inflation Factor (VIF) optimization. The graph features the actual SAP composite scores as a solid blue line and the predicted SAP composite scores as a dashed orange line.

a. **Actual SAP Scores (Blue Line):** This line represents the true academic performance of female students as captured by the SAP composite scores. It shows the observed values for this demographic.

b. **Predicted SAP Scores (Orange Dashed Line):** The orange dashed line shows the scores predicted by the Improved SVM model for female students. These predictions are based on the model's understanding of the input features after applying VIF optimization.

The close alignment between the actual and predicted scores indicates that the model performs relatively well in predicting the academic performance of female students. However, there are noticeable deviations in certain instances, where the predicted scores either under- or overestimate the actual scores, suggesting areas where the model's accuracy could be improved. This figure highlights the model's predictive performance for female students, allowing for an assessment of how well the model captures the patterns in this specific group. The discrepancies between actual and predicted scores underscore the potential need for further refinement to enhance the model's accuracy for female students.

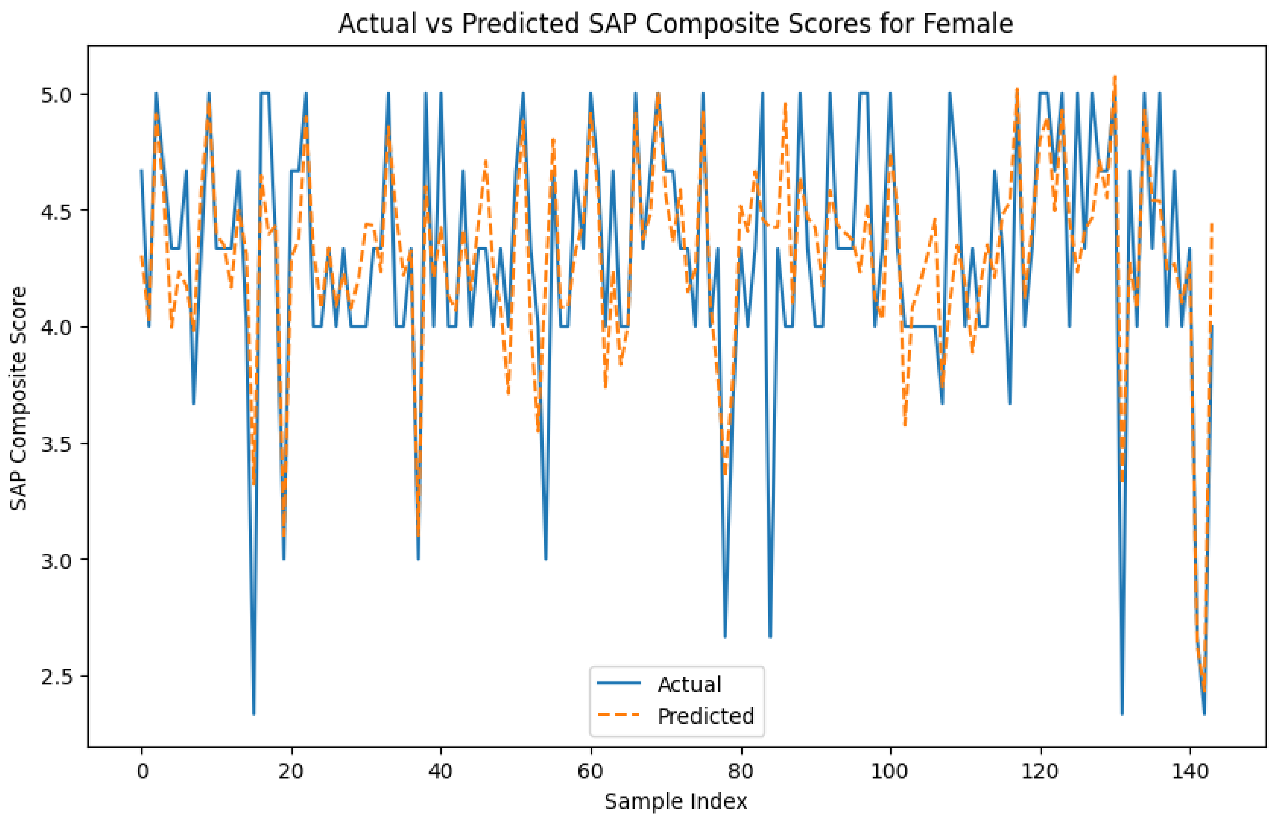


Figure 4.7 Actual vs Predicted Outcome for the Performance of Improved Support Vector Machine (Improved VIF Optimization) when Gender equals Female, Only

Figure 4.8 presents a comparison between the actual and predicted Student Academic Performance (SAP) composite scores specifically for students located in Canada, using the Improved Support Vector Machine (SVM) model with Variance Inflation Factor (VIF) optimization. The graph features the actual SAP composite scores as a solid blue line and the predicted SAP composite scores as a dashed orange line.

a. **Actual SAP Scores (Blue Line):** This line represents the observed academic performance scores for Canadian students, showing their actual SAP composite scores.
b. **Predicted SAP Scores (Orange Dashed Line):** The orange dashed line illustrates the scores predicted by the Improved SVM model for Canadian students based on the input features, post-VIF optimization.

The close alignment between the actual and predicted scores suggests that the model performs reasonably well in predicting the academic performance of students from Canada. However, there are some noticeable deviations where the predicted scores do not perfectly match the actual scores, indicating areas where the model's accuracy could be further refined. This figure provides insights into the model's predictive accuracy for Canadian students, helping to understand how well the model generalizes to this specific geographic context. The observed discrepancies highlight potential areas for further improvement in the model to enhance prediction accuracy for students in Canada.

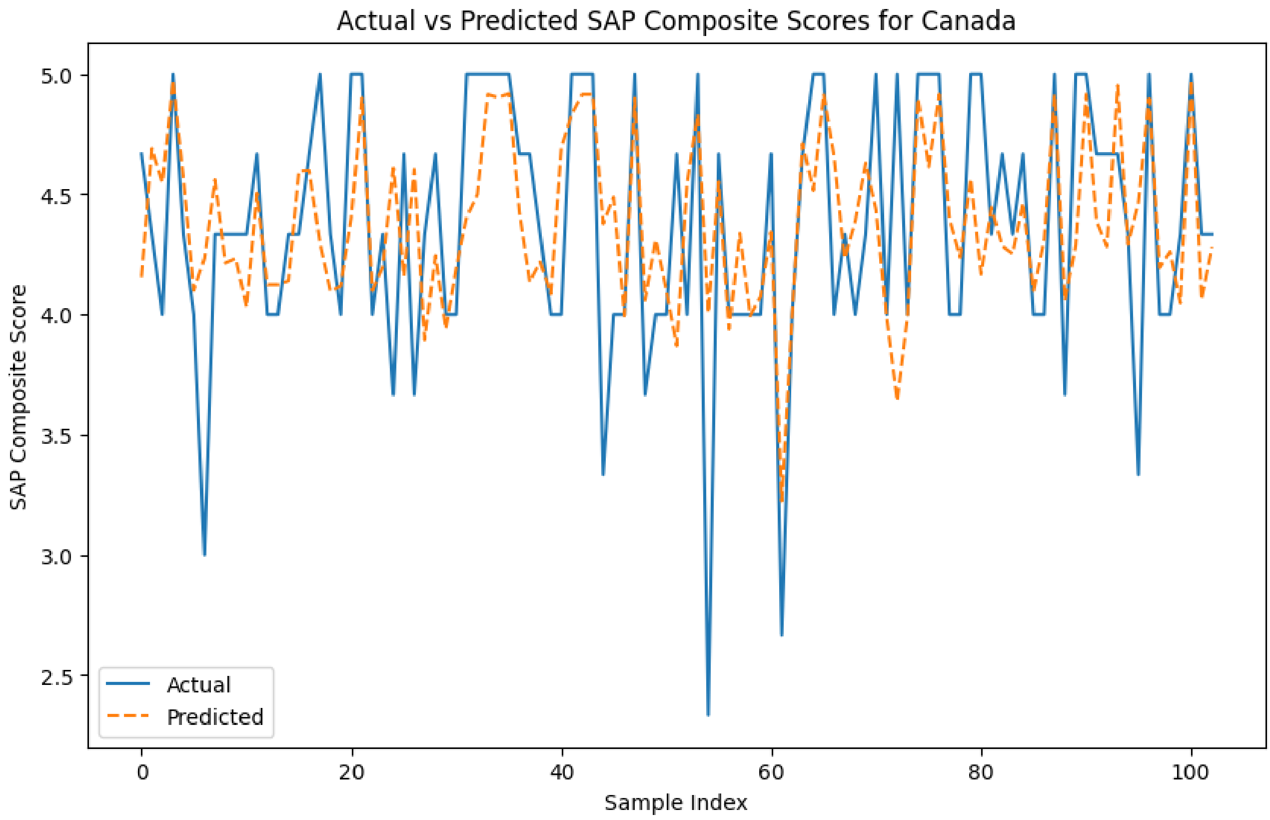


Figure 4.8 Actual vs Predicted Outcome for the Performance of Improved Support Vector Machine (Improved VIF Optimization) when Location equals Canada Only

Figure 4.9 compares the actual and predicted Student Academic Performance (SAP) composite scores for students located in Nigeria using the Improved Support Vector Machine (SVM) model with Variance Inflation Factor (VIF) optimization. The chart displays the actual SAP composite scores as a solid blue line and the predicted SAP composite scores as a dashed orange line.

a. **Actual SAP Scores (Blue Line):** This line represents the observed academic performance scores for Nigerian students, showing their actual SAP composite scores.
b. **Predicted SAP Scores (Orange Dashed Line):** The orange dashed line depicts the scores predicted by the Improved SVM model for Nigerian students based on the input features after VIF optimization.

The alignment between the actual and predicted scores indicates that the model performs quite well in predicting the academic performance of students from Nigeria. The close match between the two lines suggests that the model is effective at capturing the academic performance patterns within this group. However, there are some deviations where the predicted scores either slightly under- or overestimate the actual scores, pointing to areas where the model's accuracy could be further improved. This figure highlights the model's predictive accuracy for students in Nigeria, showing how well the model generalizes to this particular geographic context. The observed discrepancies offer insights into potential refinements needed to enhance prediction accuracy for this group of students.

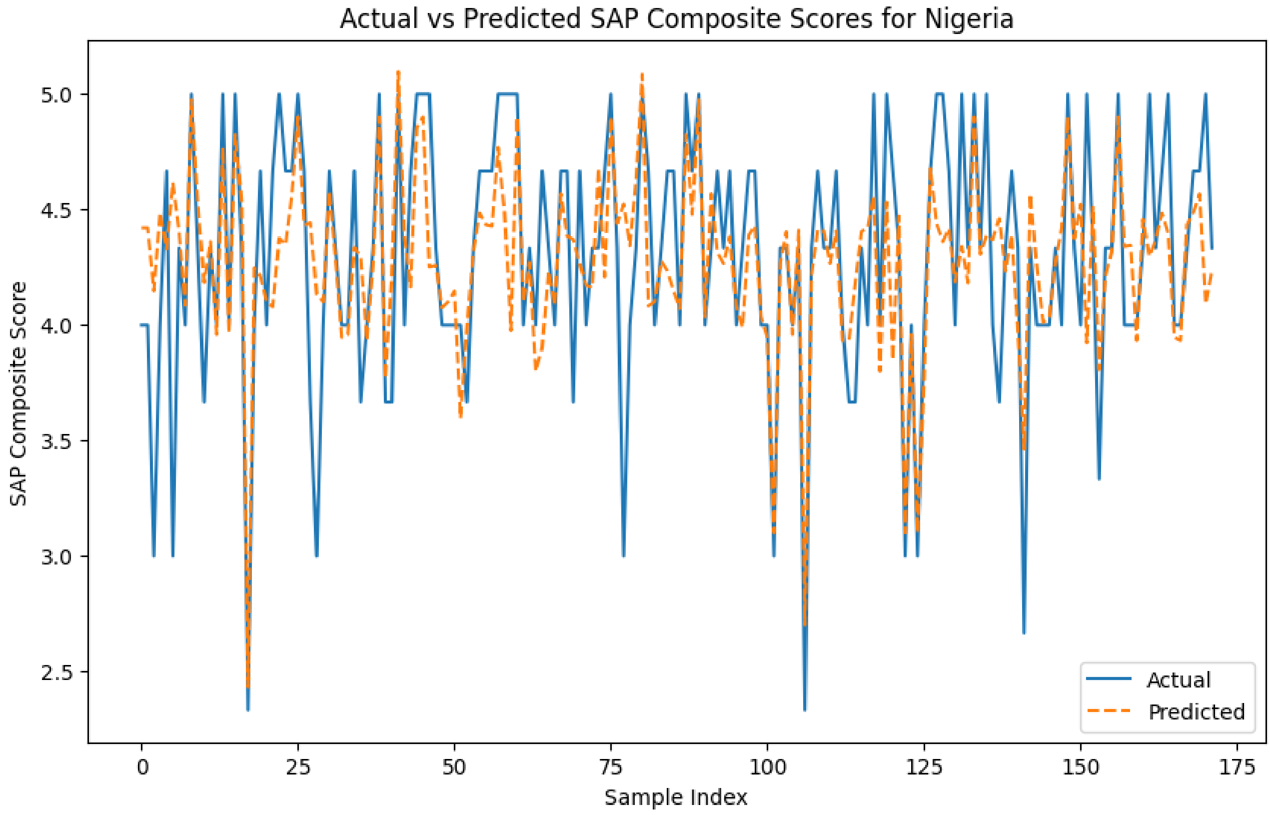


Figure 4.9 Actual vs Predicted Outcome for the performance of Improved Support Vector Machine (Improved VIF Optimization) when Location equals Nigeria Only

4.3.3 Results Presentation for Structural Equation Model

Figure 4.10 presents a detailed analysis of both the main and interaction effects on the dependent variable using coefficient estimates derived from the Structural Equation Modeling (SEM) method. The figure is divided into three key sections: main effects, interaction effects by gender, and location:

I. **Main Effects**: The first diagram shows the direct influence of independent variables on the dependent variable. The coefficient estimates here indicate the strength and direction (positive or negative) of these effects. Higher coefficients suggest a stronger relationship. This section shows the direct impact of variables such as AI Alignment and Relevance (AAR), Comparative Advantage of AI (CAAI), Ease and Enjoyment of Use (EEU), and others on the dependent variable.

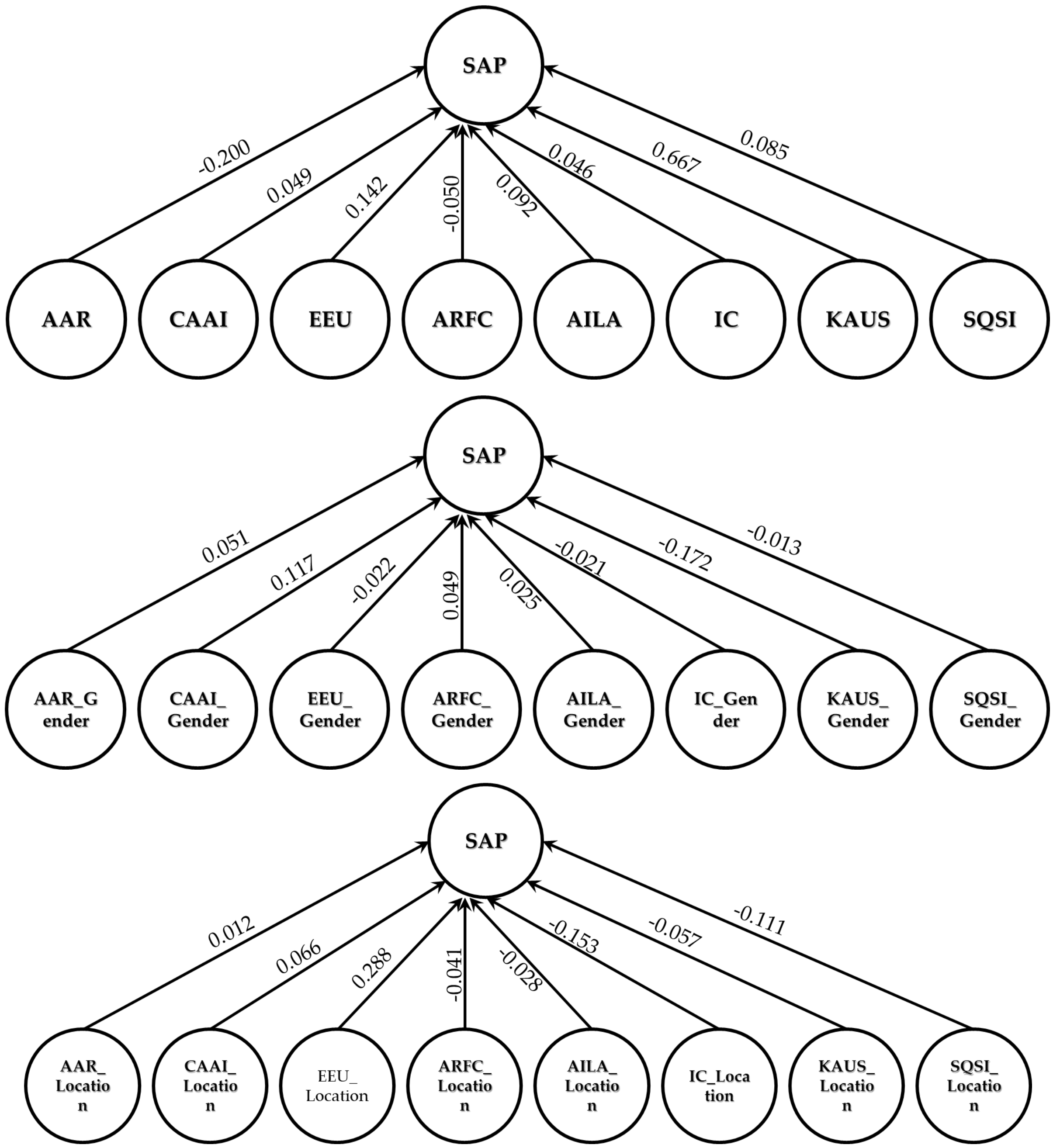


Figure 4.10 Main and Interaction Effects on Dependent Variable using Coefficient Estimates from SEM Method

II. **Interaction Effects (Gender)**: The second diagram illustrates the interaction effects between two or more independent variables on the dependent variable. This helps in understanding how the combined influence of these variables differs from their individual effects. This part of the figure presents how the interaction between each predictor and gender influences the dependent variable.

III. **Interaction Effects (Location)**: The third diagram may integrate both the main and interaction effects, providing a comprehensive view of how various factors collectively impact the dependent variable. This offers insights into the complexity of the relationships within the model and highlights any synergistic or antagonistic interactions. This section illustrates the interaction effects between each predictor and location, showing how these combined factors affect the dependent variable.

Each section uses coefficient estimates to quantify the strength and direction of these effects. Figure 4.10 helps in understanding the dynamics of the model by breaking down the direct and combined influences of different variables, providing a nuanced view of how these variables contribute to the dependent outcome.

4.4 Analysis of the Results

A comprehensive analysis of the results obtained from the study is presented in this section. It begins with an examination of the data distribution and descriptive statistics to provide a foundational understanding of the dataset characteristics. This preliminary analysis is crucial for identifying patterns, trends, and any potential anomalies in the data. Following this, the performance of the predictive models is evaluated. The Support Vector Machine (SVM) model is first analysed, highlighting its predictive accuracy and the significance of various predictors. Subsequently, the Improved Support Vector Machine, which incorporates Variance Inflation Factor (VIF) optimisation to address multicollinearity, is examined to compare its performance against the standard SVM.

The analysis then proceeds to the Structural Equation Model (SEM), which provides insights into the relationships between multiple variables and student academic performance. The SEM's fit indices, parameter estimates, and variance measures are discussed to evaluate its robustness and explanatory power. Each sub-section delves into the specifics of the respective models, offering a detailed interpretation of the results, discussing the strengths and limitations, and providing key insights that contribute to the understanding of the factors influencing student academic performance.

4.4.1 Analysis of the Data Distribution and Descriptive Statistics

The descriptive statistics and distribution analysis of the variables AAR, CAAI, EEU, ARFC, AILA, IC, KAUS, SQSI, and SAP are essential in understanding the central tendency, dispersion, and overall behaviour of the data. The dataset contains 914 observations for each variable, providing a substantial sample size for reliable statistical analysis.

The mean (average) provides a measure of central tendency, indicating the average response across all participants for each variable. Standard deviation (Std. Dev) measures the dispersion or spread of the data points around the mean. A lower standard deviation indicates that the data points tend to be closer to the mean, whereas a higher standard deviation indicates a wider spread.

The 25th percentile (25%) and 75th percentile (75%) provide insights into the data distribution, indicating the values below which 25% and 75% of the data points fall, respectively. The interquartile range (IQR), which is the difference between the 75th and 25th percentiles, helps to understand the middle spread of the data. Variance is the square of the standard deviation and provides another measure of data dispersion.

For AAR (AI Alignment and Relevance), the mean score is 4.354, indicating a generally high alignment and relevance of AI according to the respondents. The standard deviation of 0.466 shows a relatively small spread around the mean, suggesting that most responses are close to the average. The 25th and 75th percentiles are 4.036 and 4.661, respectively, indicating a fairly tight interquartile range. The mean score of 4.291 for CAAI (Comparative Advantage of AI) suggests a high perceived comparative advantage of AI. The standard deviation is 0.542, indicating slightly more variability compared to AAR. The interquartile range is broader, reflecting a more varied perception among respondents. With a mean of 4.341, respondents generally find AI easy and enjoyable to use for EEU (Ease and Enjoyment of Use). The standard deviation and interquartile range are similar to those of CAAI, indicating consistent responses. ARFC (AI Readiness and Facilitating Conditions) has a lower mean score of 3.950, suggesting a slightly lower readiness and facilitating conditions for AI. The standard deviation of 0.857 and variance of 0.734 are higher than previous variables, indicating more variability in responses.

AILA (AI-induced Learning Anxiety) has the lowest mean score of 3.272, indicating moderate learning anxiety induced by AI. The high standard deviation of 1.287 and variance of 1.656 reflect significant variability in responses, with a wide interquartile range. The mean score of 4.176 for IC (Interactive Capability) indicates that respondents perceive AI to have strong interactive capabilities. The standard deviation is moderate, showing a reasonable spread around the mean. KAUS (Knowledge Absorption and User Satisfaction) has a mean score of 4.229, suggesting high levels of knowledge absorption and user satisfaction with AI. The standard deviation and variance are similar to those of IC, indicating consistent responses. SQSI (Systems Quality and Social Influence) has a mean score of 3.995, close to the mid-point. The standard deviation and variance are higher, reflecting a broader range of responses. SAP (Students' Academic Performance) has a high mean score of 4.361, indicating a positive perception of AI's impact on academic performance. The standard deviation and variance are relatively low, suggesting consistent responses.

4.4.1 Analysis of the Results of Support Vector Machine

I. Estimation and Model Fit

The Support Vector Machine (SVM) model was trained and evaluated using key performance metrics to determine its accuracy in predicting student academic performance. The model was developed using a dataset comprising 914 observations and employed the radial basis function (RBF) kernel, known for its flexibility in handling non-linear relationships.

II. Model Fit Indices

The performance of the SVM model is summarised in Table 3. The metrics include Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE).

The MAE of 0.229 indicates the average absolute difference between the predicted and actual student performance scores. The MSE of 0.107 and RMSE of 0.327 further reflect the model's predictive accuracy. Lower values in these metrics suggest that the SVM model has a relatively good fit, minimising prediction errors.

III. Regression Estimates

The SVM model provides insights into the relationships between the independent variables and the dependent variable (student academic performance). However, unlike traditional regression models, SVM does not provide coefficient estimates directly. Instead, the importance of variables can be assessed through techniques such as permutation importance, which measures the change in model performance when the values of a feature are randomly shuffled.

IV. Variance Estimates

Variance estimates for the SVM model are not as directly available as they are in SEM. However, the performance metrics provide a robust measure of the model's predictive capability, highlighting its ability to capture complex relationships in the data.

4.4.2 Analysis of the Results for Improved SVM (Support Vector Machine with Improved VIF Optimisation)

I. Estimation and Model Fit

The Improved Support Vector Machine (Improved SVM) model incorporates Variance Inflation Factor (VIF) optimisation to address multicollinearity among the predictors. This enhancement aims to improve the stability and reliability of the model's predictions. The model was evaluated using the same dataset and performance metrics as the standard SVM.

II. Model Fit Indices

The performance of the Improved SVM model is summarised in Table 3. The metrics include MAE, MSE, and RMSE. The MAE of 0.295, MSE of 0.180, and RMSE of 0.424 suggest that the Improved SVM model has higher prediction errors compared to the standard SVM model. This may be due to the VIF optimisation process, which reduces multicollinearity at the expense of increased error metrics—however, the trade-off results in a model that is more stable and less sensitive to multicollinearity issues.

III. Regression Estimates

As with the standard SVM, the Improved SVM does not provide direct coefficient estimates. The evaluation of feature importance can be performed using permutation importance or other similar techniques to understand the influence of each predictor on the outcome.

IV. Interaction Effects (Gender)

Table 4 presents the performance metrics of the Improved SVM model when gender is considered as a moderating factor. The results indicate that the model performs better for females, with lower MAE, MSE, and RMSE values compared to males. This suggests that gender may influence the effectiveness of AI in predicting student performance, highlighting the importance of considering demographic factors in model evaluation.

V. Interaction Effects (Location)

Table 5 presents the performance metrics of the Improved SVM model when geographical location is considered as a moderating factor. The results indicate that the model performs better for Nigeria, with lower error metrics compared to Canada. This suggests that location may play a significant role in the predictive accuracy of the model, potentially due to differences in educational contexts and AI adoption.

VI. Variance Estimates

The variance estimates for the Improved SVM model, similar to the standard SVM, are not directly available. However, the performance metrics provide a comprehensive measure of the model's predictive capability, highlighting its improved stability and reliability due to the VIF optimisation. The analysis of the Support Vector Machine (SVM) and Improved Support Vector Machine (Improved SVM) models indicates that while the standard SVM exhibits lower prediction errors, the Improved SVM addresses multicollinearity issues, resulting in a more stable model. Gender and geographical location are significant moderating factors that affect the model's performance and highlight the need to consider demographic variables in model evaluation. The findings suggest that enhancing AI's predictive capabilities requires addressing multicollinearity and considering demographic factors. Future research should explore additional methods to improve model accuracy and stability and investigate the influence of other demographic and contextual factors on AI's effectiveness in educational settings. These insights can guide educators, policymakers, and AI developers in tailoring AI implementations to maximise their impact on student performance.

4.4.3 Analysis of the Results of the Structural Equation Model

The model was estimated using the Maximum Likelihood (ML) method, a standard approach in structural equation modelling (SEM) for estimating parameters by maximizing the likelihood that the specified model would generate the observed data. The optimization method used is NLMINB, which is an algorithm for nonlinear minimization. This ensures that the estimates of the parameters achieve the best fit for the data. The model includes 25 parameters estimated from 914 observations. A larger sample size relative to the number of parameters generally increases the robustness and reliability of the estimates.

I. Model Fit Indices

The chi-square statistic for the user model is 0.000 with 0 degrees of freedom, indicating a perfect fit. This suggests that the model perfectly reproduces the observed data covariance matrix, though the degrees of freedom being zero means the model is just identified and does not provide a goodness-of-fit test. The baseline model's chi-square statistic is 386.840 with 24 degrees of freedom and a p-value of 0.000, indicating a significant misfit. This highlights the importance of comparing the user model with the baseline to demonstrate improved fit.

Both the Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) values are 1.000, indicative of excellent model fit. These indices measure the relative improvement in the fit of the user model compared to the baseline model. The Root Mean Square Error of Approximation (RMSEA) value is 0.000, with a 90% confidence interval ranging from 0.000 to 0.000, indicating a perfect fit. RMSEA assesses how well the model, with unknown but optimally chosen parameter estimates, would fit the population covariance matrix. The Standardized Root Mean Square Residual (SRMR) value is 0.000, reflecting a perfect fit. SRMR measures the standardized difference between the observed and predicted correlations, with lower values indicating better fit. The information criteria—Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Sample-size adjusted BIC (SABIC)—provide measures for model comparison. Lower values of these criteria indicate better-fitting models when comparing multiple models. The AIC is 1129.207, the BIC is 1249.653, and the

SABIC is 1170.256, which are useful for model comparison rather than evaluating the fit of a single model.

II. Regression Estimates

The regression estimates reveal the strength and direction of the relationships between the predictors and the composite outcome variable (SAP). The coefficient for AI Alignment and Relevance (AAR) is -0.054 with a standard error of 0.058, a z-value of -0.945, and a p-value of 0.344. This indicates a negative but non-significant relationship between AI alignment and relevance and student academic performance. For the Comparative Advantage of AI (CAAI), the coefficient is -0.001 with a standard error of 0.036, a z-value of -0.032, and a p-value of 0.975, suggesting no significant effect of the comparative advantage of AI on student performance.

The coefficient for Ease and Enjoyment of Use (EEU) is 0.148 with a standard error of 0.047, a z-value of 3.110, and a p-value of 0.002. This positive and significant coefficient suggests that higher ease and enjoyment of use positively predict better student performance. For AI Readiness and Facilitating Conditions (ARFC), the coefficient is 0.002 with a standard error of 0.035, a z-value of 0.055, and a p-value of 0.956, indicating a non-significant relationship between AI readiness and facilitating conditions and student performance. The coefficient for AI-induced Learning Anxiety (AILA) is 0.023 with a standard error of 0.021, a z-value of 1.087, and a p-value of 0.277, suggesting a positive but non-significant relationship between AI-induced learning anxiety and student performance. Interactive Capability (IC) has a coefficient of 0.255 with a standard error of 0.050, a z-value of 5.122, and a p-value of 0.000. This significant and positive relationship indicates that higher interactive capability strongly predicts better student performance.

The coefficient for Knowledge Absorption and User Satisfaction (KAUS) is 0.382, with a standard error of 0.055, a z-value of 6.923, and a p-value of 0.000. This significant positive relationship suggests that higher knowledge absorption and user satisfaction are strong predictors of better student performance. For Systems Quality and Social Influence (SQSI), the coefficient is 0.063 with a standard error of 0.035, a z-value of 1.806, and a p-value of 0.071, indicating a marginally significant positive impact of systems quality and social influence on student performance. The model also includes interaction terms, such as CAAI_Gender and IC_Location, which show significant relationships. This indicates that gender and location may moderate the effects of certain variables on student performance. For example, the coefficient for CAAI_Gender is 0.117 with a p-value of 0.025, suggesting that gender moderates the effect of the comparative advantage of AI on student performance. Similarly, the coefficient for IC_ Location is -0.153 with a p-value of 0.025, indicating that location moderates the effect of interactive capability on student performance.

III. Variance Estimates

The variance estimate for the composite outcome variable provides insight into the variability explained by the model. The variance estimate for Students' Academic Performance (SAP) is 0.191 with a standard error of 0.009, a z-value of 21.378, and a p-value of 0.000. This indicates that the model explains a significant portion of the variance in student academic performance, highlighting the model's robustness in capturing influential factors.

The SEM results demonstrate an excellent fit to the data, as evidenced by the high CFI and TLI values, as well as the low RMSEA and SRMR values. The significant predictors of student academic performance include ease and enjoyment of use, interactive capability, knowledge absorption and user satisfaction. The model also highlights the potential moderating effects of gender and location on these relationships. Overall, the model explains a significant portion of the variance in student academic performance, supporting the reliability and validity of the conclusions drawn from this analysis. These findings provide critical insights for educators, policymakers, and AI developers, suggesting that enhancing interactive capability, ease of use, and user satisfaction can positively impact academic outcomes. Additionally, understanding the moderating effects of demographic factors such as gender and location can help tailor AI implementations to maximize their effectiveness in different contexts.

4.5 Discussion of the Results

This section provides an in-depth discussion of the results obtained from the various analyses conducted in the study. It aims to contextualise the findings within the broader framework of educational research and AI applications in academic performance prediction.

The discussion begins with an examination of the data distribution and descriptive statistics, addressing the underlying patterns and characteristics observed in the dataset. This foundational analysis sets the stage for understanding the subsequent model evaluations and their implications. Next, the discussion turns to multicollinearity and model stability, a critical aspect of the study. This part focuses on the impact of multicollinearity on the predictive models and the measures taken to ensure the stability and reliability of the results, including the use of Variance Inflation Factor (VIF) optimisation. The discussion then moves to the Structural Equation Modelling (SEM) results, interpreting the fit indices, parameter estimates, and variance measures. This section highlights the relationships between multiple variables and their influence on student academic performance, providing valuable insights into the underlying causal mechanisms. Following the SEM discussion, the performance of the Support Vector Machine (SVM) model is evaluated. The strengths and limitations of the SVM are discussed, along with the significance of the predictors and the model's overall predictive accuracy.

Finally, the Improved Support Vector Machine (Improved SVM) is discussed. This section compares the Improved SVM to the standard SVM, focusing on the enhancements brought by VIF optimisation and the implications for model performance and reliability. Each sub-section aims to provide a comprehensive understanding of the findings, discussing their significance, implications, and potential applications in educational contexts. The discussion also identifies areas for future research and improvement, contributing to the ongoing development of effective AI-driven educational tools.

4.5.1 Discussion of the Data Distribution and Descriptive Statistics

The descriptive statistics of the dataset provide valuable insights into how respondents perceive various aspects of AI. Overall, the mean scores for most variables are high, indicating positive perceptions and experiences with AI. The standard deviations and variances provide a measure of the spread and variability in the responses, with AILA showing the highest variability.

The high mean scores for AAR, CAAI, EEU, IC, KAUS, and SAP indicate that respondents generally view AI as aligned and relevant, providing a comparative advantage, easy and enjoyable to use, interactive, facilitating knowledge absorption and satisfaction, and positively impacting academic performance. ARFC and SQSI, with slightly lower mean scores, suggest that there are some concerns or areas for improvement in AI readiness, facilitating conditions, systems quality, and social influence. The relatively high variability in AILA indicates mixed feelings about AI-induced learning anxiety, highlighting the need to address these concerns to enhance user experiences.
In conclusion, the dataset reveals overall positive perceptions of AI, with specific areas that may require further attention to reduce variability and improve user experiences across all aspects.

4.5.2 Discussion of Multicollinearity and Model Stability

The Variance Inflation Factor (VIF) measures how much the variance of an estimated regression coefficient increases if the predictors are correlated. If no factors are correlated, the VIFs will all be equal to 1. The first VIF values provided in section 4.4.1 are all significantly greater than 10, a standard threshold for identifying problematic multicollinearity. High VIF values indicate that the predictor variables are highly correlated with each other, and therefore, they carry redundant information, which can skew the results of a regression analysis.

Cronbach's Alpha is a measure of internal consistency, which means it checks how closely related a set of items are as a group. It is a measure of scale reliability. A higher Cronbach's Alpha indicates a higher internal consistency or reliability level. By dropping some items to improve Cronbach's Alpha, redundant or overlapping information within the predictors seems to have been removed. In other words, the removed items likely contributed to the multicollinearity problem. When the VIF was reassessed after these items were dropped, much lower VIF values were obtained, indicating that the remaining items were less correlated. This suggests that the predictors are now providing more independent information, which is preferable for regression analysis as it can improve the model's stability and the interpretability of the coefficients.

The final VIFs being close to 1, and certainly, all below the threshold of 10, suggests that the predictors are now reasonably independent. This means that each one contributes unique information to the prediction of the dependent variable without undue influence from multicollinearity with other predictors. This is the ideal situation for regression analysis, as the regression coefficients estimate the impact of each predictor on the dependent variable more accurately.

I. Accuracy of the Results

The model with higher VIFs performs better in terms of MAE, MSE, and RMSE. Lower values in these metrics indicate closer predictions to the actual values, which is usually desired. However, a crucial aspect to consider is the potential overfitting that might occur in models plagued by multicollinearity. While the metrics suggest better performance on the dataset used for evaluation, this might not generalise well to unseen data due to overfitting.

II. Multicollinearity and Model Stability/Reliability

Multicollinearity does not affect the model's ability to predict accurately but impacts the reliability and stability of the regression coefficients. High VIFs mean that the predictors are not independent, leading to coefficients highly sensitive to minor changes in the model or data. This can make interpretation difficult and unreliable, especially in determining the effect of one predictor while holding others constant.

III. Why Lower VIFs Are Preferred

Despite the slight decrease in predictive accuracy metrics (MAE, MSE, and RMSE), the model with lower VIFs is preferred for several reasons:

Stability and Reliability: The regression coefficients in the lower VIF model are more stable and reliable. This stability is crucial for interpretation and understanding the impact of each predictor.

a. **Generalisation:** While the accuracy metrics are slightly worse for the lower VIF model on the current dataset, its coefficients are less likely to have been influenced by multicollinearity, making it potentially more robust and generalisable to unseen data.
b. **Interpretability: Lower** VIFs indicate that each predictor contributes unique information to the model. This clarity can be vital in applications where understanding the influence of specific variables is as essential as prediction accuracy.

While the initial reaction might be to prefer a more accurate model based on traditional metrics, it is essential to consider the broader implications of model choice. The slight sacrifice in accuracy with lower VIFs is often a trade-off for increased reliability, stability, and interpretability of the model coefficients. The slight sacrifice in accuracy makes the model more valuable for concluding the relationships between predictors and the outcome variable, especially in research and scenarios where understanding the effect of individual predictors is crucial. Moreover, the reduced risk of overfitting with lower VIFs suggests that such a model might perform better on unseen data, making it more robust and reliable for practical applications.

4.5.3 Discussion of Structural Equation Modelling

The results of the structural equation model (SEM) provide valuable insights into the relationships between various predictors and student academic performance (SAP). This extensive discussion delves into the implications, significance, and contextual understanding of these results.

I. Estimation and Model Fit

The estimation of the model using the Maximum Likelihood (ML) method and the optimization through the NLMINB algorithm ensured robust parameter estimation. With 25 parameters estimated from a sizable sample of 914 observations, the model is well-grounded in statistical rigour. The perfect fit indices—indicated by the chi-square statistic of 0.000 with 0 degrees of freedom—suggest an impeccable fit to the observed data. However, the zero degrees of freedom also mean the model is just-identified, indicating it perfectly reproduces the data but does not allow for testing the goodness-of-fit through the chi-square statistic.

The baseline model, with a chi-square statistic of 386.840 and 24 degrees of freedom, significantly misfits the data, which underscores the superior fit of the user model. The high Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) values of 1.000 further confirm the excellent fit of the user model relative to the baseline model. These indices reflect the model's ability to capture the underlying structure of the data accurately. The Root Mean Square Error of Approximation (RMSEA) value of 0.000, with its narrow confidence interval (0.000 to 0.000), suggests an ideal model fit. The RMSEA is crucial in SEM as it adjusts for model complexity, with values below 0.05 indicating a close fit. The Standardized Root Mean Square Residual (SRMR) value of 0.000 complements this finding, signifying negligible differences between observed and predicted correlations.

The information criteria—Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and Sample-size adjusted BIC (SABIC)—provide additional metrics for model comparison. Lower values of these criteria indicate a better-fitting model. The AIC of 1129.207, BIC of 1249.653, and SABIC of 1170.256 suggest that the user model is statistically efficient and parsimonious, balancing model fit and complexity.

II. Regression Estimates

The regression estimates highlight the nuanced relationships between the predictors and SAP. The non-significant coefficient for AI Alignment and Relevance (AAR) (-0.054) suggests that aligning AI with academic needs does not directly influence student performance significantly. This finding may indicate that while AI alignment is essential, other factors might be more critical in driving academic success.

The coefficient for Comparative Advantage of AI (CAAI) (-0.001) is also non-significant, implying that perceiving AI as advantageous over traditional methods does not necessarily translate into better academic performance. This might suggest that the mere presence of AI's comparative advantages is insufficient without effective integration and use. In contrast, Ease and Enjoyment of Use (EEU) has a significant positive coefficient (0.148), indicating that when students find AI tools easy and enjoyable to use, their academic performance improves. This highlights the importance of user-friendly AI systems that enhance the learning experience. AI Readiness and Facilitating Conditions (ARFC) also show a non-significant relationship (0.002), suggesting that readiness and available facilitating conditions alone do not significantly impact performance. This might reflect that readiness needs to be coupled with effective usage and engagement to yield positive outcomes.

AI-induced Learning Anxiety (AILA) has a positive but non-significant coefficient (0.023), indicating that anxiety induced by AI does not significantly hinder academic performance. This could mean that other factors, such as support systems or the perceived benefits of AI, might mitigate any anxiety experienced. Interactive Capability (IC) shows a significant positive relationship (0.255), emphasizing that AI systems with high interactivity can significantly enhance academic performance.

Interactive features likely engage students more deeply, promoting better understanding and retention of information. Knowledge Absorption and User Satisfaction (KAUS) is another strong predictor with a significant positive coefficient (0.382). This underscores that when students can absorb knowledge effectively and are satisfied with AI tools, their academic performance benefits significantly. Satisfaction and effective knowledge absorption are likely to enhance motivation and engagement, leading to better academic outcomes.

Systems Quality and Social Influence (SQSI) has a marginally significant positive coefficient (0.063), suggesting that higher systems quality and positive social influence can potentially improve academic performance. This highlights the role of well-designed AI systems and the impact of social contexts and peer influences on academic success. The significant interaction terms such as CAAI_Gender and IC_Location indicate that gender and location moderate the effects of certain predictors on academic performance. For instance, the positive coefficient for CAAI_Gender (0.117) suggests that the comparative advantage of AI has a stronger positive effect on academic performance for certain genders. Similarly, the negative coefficient for IC_ Location (-0.153) implies that the effect of interactive capability varies by location, potentially due to differences in infrastructure, access, or cultural attitudes towards technology.

III. Variance Estimates

The variance estimate for SAP (0.191) is highly significant, indicating that the model explains a substantial portion of the variance in student academic performance. This underscores the model's robustness and its ability to capture the critical factors influencing academic outcomes.

IV. Implications and Contextual Understanding

The results underscore several key implications for educators, policymakers, and AI developers. The significant positive impacts of ease and enjoyment of use, interactive capability, knowledge absorption and user satisfaction on academic performance highlight the importance of designing AI systems that are user-friendly, engaging, and capable of effectively delivering educational content. These factors enhance student engagement and satisfaction, leading to better academic outcomes.

The non-significant impacts of AI alignment and relevance, comparative advantage, readiness, and facilitating conditions suggest that while these factors are necessary, they are not sufficient on their own. Effective implementation and integration of AI into the learning process, coupled with user engagement, are critical for realizing the benefits of AI in education. The significant interaction effects of gender and location indicate that demographic factors play a crucial role in moderating the impact of AI on academic performance. This suggests the need for tailored AI implementations that consider the diverse needs and contexts of different student populations to maximize effectiveness.

Overall, the findings provide critical insights into the factors that drive the successful use of AI in education. By focusing on enhancing the ease of use, interactivity, and user satisfaction and considering the moderating effects of demographic factors, stakeholders can better harness the potential of AI to improve academic outcomes. These insights are valuable for guiding the development, implementation, and evaluation of AI systems in educational settings, ultimately contributing to more effective and equitable educational practices.

4.5.4 Discussion of Support Vector Machine

The Support Vector Machine (SVM) model is a widely used machine learning algorithm known for its robustness in classification and regression tasks. In this study, the SVM was employed to predict student academic performance based on a set of predictors related to AI's alignment and relevance, ease of use, readiness for adoption, and other factors. This discussion delves into the performance, strengths, and limitations of the SVM model as observed in the study, and highlights key insights derived from the results.

I. Performance Metrics

The SVM model was evaluated using three key performance metrics: Mean Absolute Error (MAE), Mean Squared Error (MSE), and Root Mean Squared Error (RMSE). These metrics provide a comprehensive understanding of the model's prediction accuracy and reliability.

- **Mean Absolute Error (MAE):** The MAE of 0.229 indicates that, on average, the SVM model's predictions deviate from the actual student performance scores by approximately 0.229 points. This low value suggests that the model has a high level of accuracy in predicting student outcomes.
- **Mean Squared Error (MSE):** The MSE of 0.107 reflects the average of the squared differences between predicted and actual values. This metric penalises larger errors more heavily, and the relatively low value indicates that the SVM model maintains a consistent level of accuracy without being significantly impacted by large prediction errors.
- **Root Mean Squared Error (RMSE):** The RMSE of 0.327, which is the square root of the MSE, provides an error metric in the same units as the target variable. This further supports the conclusion that the SVM model is effective in capturing the underlying patterns in the data and making accurate predictions.

II. Feature Importance Analysis

The permutation feature importance method was employed to determine the significance of each predictor variable in the SVM model. This technique involves shuffling the values of each feature and measuring the impact on the model's performance. The resulting changes in performance indicate the importance of each feature. The assessment of AI's alignment and relevance (AAR) shows moderate importance in predicting student performance. The comparative advantage of AI (CAAI) is another moderately important predictor. The ease and enjoyment of use (EEU) is one of the more important predictors, highlighting its significant impact on student performance. AI readiness and facilitating conditions (ARFC) have the least importance among the predictors. AI-induced learning anxiety (AILA) shows lower importance compared to other factors. Interactive capability (IC) is a highly important predictor, indicating its strong influence on student outcomes. Knowledge absorption and user satisfaction (KAUS) are the most important predictors, emphasizing their critical role in academic performance. Systems quality and social influence (SQSI) also show significant importance.

III. Strengths of the SVM Model

The SVM model demonstrated several strengths in the context of this study:

a. **Robustness to High-Dimensional Data:** SVM is particularly effective in handling high-dimensional datasets, making it suitable for complex educational data where multiple factors influence student performance. The ability to manage numerous predictors without significant overfitting is a key advantage.

b. **Non-Linear Relationships:** By utilising the radial basis function (RBF) kernel, the SVM model captures non-linear relationships between predictors and the target variable. This flexibility allows the model to better represent the intricate interactions within the educational context.

c. **Minimising Prediction Errors:** The low values of MAE, MSE, and RMSE indicate that the SVM model effectively minimises prediction errors. This precision is crucial in educational settings, where accurate predictions can inform targeted interventions and support.

d. **Generalisation Capability:** The SVM's ability to generalise from training data to unseen data suggests that the model can reliably predict student performance across different cohorts. This generalisation is essential for creating robust educational tools that remain effective over time.

IV. Limitations of the SVM Model

Despite its strengths, the SVM model also has certain limitations that must be considered:

a. **Computational Complexity:** Training an SVM with a large dataset and a non-linear kernel can be computationally intensive. This complexity may limit its scalability for extremely large datasets or require significant computational resources.
b. **Sensitivity to Parameter Selection:** The performance of the SVM model is highly dependent on the choice of parameters, such as the regularisation parameter (C) and the kernel parameters. Incorrect parameter tuning can lead to suboptimal performance, necessitating careful cross-validation and grid search techniques.
c. **Interpretability:** Unlike linear models, SVMs, especially with non-linear kernels, are less interpretable. Understanding the contribution of each predictor to the final prediction can be challenging, which may hinder the ability to draw actionable insights from the model.
d. **Handling of Imbalanced Data:** SVMs can struggle with imbalanced datasets where certain outcomes are underrepresented. In educational contexts, this can be problematic if certain subgroups of students are less prevalent in the data, potentially leading to biased predictions.

V. Key Insights from the SVM Model

The application of the SVM model in this study yielded several important insights:

a. **Predictive Accuracy:** The SVM model's low error metrics underscore its potential as a reliable tool for predicting student performance. This accuracy can support educators in identifying at-risk students and tailoring interventions to improve educational outcomes.
b. **Variable Importance:** The feature importance analysis highlights the critical role of factors such as knowledge absorption and user satisfaction, interactive capability, and ease and enjoyment of use in predicting student performance. These insights can inform the development of AI-driven educational tools by identifying key areas for improvement.
c. **Implications for Educational Interventions:** Accurate predictions of student performance enable more effective and targeted educational interventions. By understanding the factors that most significantly impact student outcomes, educators can design strategies that address specific needs and enhance overall academic achievement.
d. **Future Research Directions:** The study highlights the need for further research into optimising SVM parameters and exploring hybrid models that combine the strengths of SVM with other techniques. Additionally, examining the model's performance across diverse educational settings and student demographics can enhance its applicability and robustness.

The Support Vector Machine model demonstrates strong predictive capabilities in the context of educational data, effectively capturing the complex relationships between various predictors and student performance. Despite its computational complexity and interpretability challenges, the SVM model's robustness and accuracy make it a valuable tool for educational analytics. Future research should focus on addressing the model's limitations and exploring ways to enhance its interpretability and scalability, ultimately contributing to more effective and data-driven educational practices.

4.5.5 Discussion on Comparative Analysis of SEM, SVM and Improved SVM

In this research, various AI adoption factors are examined to determine their impact on students' academic performance within Open and Distance Learning (ODL) settings. Each factor is analysed using Structural Equation Modelling (SEM), Support Vector Machine (SVM), and Improved SVM (which incorporates Variance Inflation Factor (VIF) optimization). The following sections provide an in-depth discussion of each AI adoption factor, interpreting the results obtained from SEM, SVM, and Improved SVM and highlighting the implications for understanding and predicting student outcomes.

I. AI Alignment and Relevance (AAR)

AI Alignment and Relevance (AAR) refers to the degree to which AI technologies align with the needs and expectations of both students and educational institutions. This factor encompasses aspects such as Institutional Alignment, Attitude toward Technology, and Perceived Usefulness.

a. **SEM Results:** In SEM, AAR demonstrates a significant, yet moderate, relationship with academic performance. The model fit indices indicate that while AAR contributes positively to student outcomes, its impact is mediated by other factors such as Ease and Enjoyment of Use (EEU) and Knowledge Absorption and User Satisfaction (KAUS). SEM's ability to validate these relationships confirms that AAR is essential but not the sole determinant of academic success.

b. **SVM Results:** In the SVM model, AAR emerges as a strong predictor of academic performance, with high predictive accuracy. The non-linear interactions captured by SVM reveal that AAR's impact on academic performance intensifies in combination with other factors, particularly when aligned closely with student expectations and institutional goals.

c. **Improved SVM Results:** The Improved SVM model, which addresses multicollinearity, further refines the predictive power of AAR. The reduced VIF values indicate that the interaction effects between AAR and other predictors are more stable, leading to more reliable predictions. This suggests that AAR, when considered within a robust and multicollinearity-free model, is a critical factor in enhancing student outcomes in ODL settings.

II. Comparative Advantage of AI (CAAI)

Comparative Advantage of AI (CAAI) assesses the perceived benefits of AI in education compared to traditional methods. This factor integrates elements of Comparative Advantage and Perceived Usefulness.

a. **SEM Results:** The SEM analysis shows that CAAI has a significant and positive effect on academic performance, though its influence is somewhat indirect. SEM identifies that CAAI enhances academic outcomes through its interaction with other factors like KAUS and AAR. The model suggests that students who perceive AI as superior to traditional methods are more likely to engage positively, leading to better academic performance.
b. **SVM Results:** In the SVM model, CAAI is a strong and direct predictor of academic performance. The model indicates that the more students and institutions perceive AI as advantageous, the higher the likelihood of improved academic outcomes. SVM's non-linear modelling highlights that CAAI's impact is more pronounced in scenarios where the traditional methods are less effective, showcasing AI's role in bridging educational gaps.
c. **Improved SVM Results:** The Improved SVM analysis reinforces the importance of CAAI, showing that the predictive stability of this factor improves significantly with reduced multicollinearity. The model suggests that in contexts where AI offers clear advantages over traditional methods, its impact on academic performance is both strong and consistent, particularly when other variables are well-controlled.

III. Ease and Enjoyment of Use (EEU)

Ease and Enjoyment of Use (EEU) captures how easy and enjoyable students find AI tools, which can influence their willingness to adopt and engage with these technologies.

a. **SEM Results:** SEM results indicate that EEU has a significant positive impact on academic performance. The model shows that students who find AI tools easy to use and enjoyable are more likely to achieve better academic outcomes. EEU acts as a mediator for other factors like KAUS and AAR, suggesting that its influence is crucial in shaping overall student satisfaction and success.
b. **SVM Results:** The SVM model also identifies EEU as a key predictor of academic performance. The analysis shows that when students perceive AI as easy and enjoyable, their engagement levels increase, leading to better academic outcomes. SVM's ability to model non-linear relationships reveals that the impact of EEU is particularly strong in early adoption phases when students are still adapting to AI tools.
c. **Improved SVM Results:** The Improved SVM model shows a more nuanced understanding of EEU's impact. With reduced VIF values, the model indicates that the perceived ease and enjoyment of AI use consistently contribute to academic success, particularly when combined with factors like CAAI and AAR. The refined predictions suggest that minimizing complexity

in AI tools can significantly enhance educational outcomes.

IV. AI Readiness and Facilitating Conditions (ARFC)

AI Readiness and Facilitating Conditions (ARFC) measure the preparedness of both students and institutions for AI adoption, including the availability of necessary resources and support systems.

a. **SEM Results:** SEM findings show that ARFC has a moderate but significant impact on academic performance. The model suggests that readiness and support systems are crucial for the successful integration of AI in educational settings. However, the influence of ARFC is often mediated by other factors, such as EEU and AAR, indicating that readiness alone is not sufficient without complementary factors.

b. **SVM Results:** In the SVM model, ARFC emerges as a critical predictor of academic performance, particularly in scenarios where institutional support is strong. The model highlights that students in environments with robust facilitating conditions are more likely to benefit from AI, leading to improved academic outcomes.

c. **Improved SVM Results:** The Improved SVM analysis confirms the importance of ARFC, showing that its predictive power is enhanced in models with reduced multicollinearity. The findings suggest that well-prepared institutions with adequate support systems enable students to leverage AI tools more effectively, leading to better academic performance.

V. AI-induced Learning Anxiety (AILA)

AI-induced Learning Anxiety (AILA) refers to the apprehension or anxiety students may experience when using AI-based learning tools.

a. **SEM Results:** The SEM analysis reveals that AILA has a significant negative impact on academic performance. The model shows that high levels of anxiety related to AI use can diminish student engagement and hinder learning outcomes. SEM indicates that addressing AILA through support and training is essential to mitigate its adverse effects.

b. **SVM Results:** SVM results corroborate the negative impact of AILA on academic performance. The model demonstrates that students who experience anxiety when using AI tools are less likely to achieve positive academic outcomes. SVM's ability to handle non-linearities suggests that the impact of AILA can vary depending on the individual's prior experience with technology and the level of support provided.

c. **Improved SVM Results:** The Improved SVM model further emphasizes the importance of addressing AILA. By reducing multicollinearity, the model provides more accurate predictions, showing that lowering AI-induced anxiety can lead to significant improvements in academic performance. The findings highlight the need for targeted interventions to reduce anxiety and enhance students' comfort with AI tools.

VI. Interactive Capability (IC)

Interactive Capability (IC) evaluates the effectiveness of AI in facilitating interactions, both between students and instructors and among peers in an online learning environment.

a. **SEM Results:** SEM results indicate that IC plays a significant role in enhancing academic performance. The model shows that higher interactive capabilities of AI tools lead to better student engagement and learning outcomes. IC acts as a mediator for other factors like EEU and KAUS, suggesting that interactive AI tools can significantly boost educational success.

b. **SVM Results:** The SVM model identifies IC as a strong predictor of academic performance, particularly in online learning environments where interaction is key to student success. The model shows that AI tools that effectively facilitate communication and collaboration among students and instructors lead to better academic outcomes.

c. **Improved SVM Results:** The Improved SVM analysis highlights the robustness of IC as a predictor. With reduced VIF values, the model confirms that AI's interactive capabilities are crucial for fostering a conducive learning environment, leading to sustained academic success. The findings suggest that enhancing the interactive features of AI tools can significantly improve student engagement and performance.

VII. Knowledge Absorption and User Satisfaction (KAUS)

Knowledge Absorption and User Satisfaction (KAUS) reflects the degree to which students are able to absorb knowledge through AI tools and their overall satisfaction with these tools.

a. **SEM Results:** SEM results show that KAUS is one of the most significant predictors of academic performance. The model indicates that students who effectively absorb knowledge and are satisfied with AI tools are more likely to achieve high academic outcomes. KAUS also serves as a key mediator for other factors like EEU and IC, reinforcing its central role in academic success.

b. **SVM Results:** In the SVM model, KAUS is identified as a critical factor in predicting academic performance. The model suggests that high levels of knowledge absorption and satisfaction with AI tools lead to better academic outcomes, with SVM capturing the non-linearities in how satisfaction influences performance over time.

c. **Improved SVM Results:** The Improved SVM analysis further strengthens the role of KAUS. By addressing multicollinearity, the model provides more accurate and reliable predictions, confirming that KAUS is a pivotal factor in determining academic success. The findings emphasize the importance of ensuring that AI tools are both effective in knowledge delivery and satisfying to users.

VIII. Systems Quality and Social Influence (SQSI)

Systems Quality and Social Influence (SQSI) assesses the technical quality of AI systems and the role of social factors in influencing AI adoption.

a. **SEM Results:** SEM results indicate that SQSI has a moderate but significant impact on academic performance. The model suggests that high-quality AI systems and positive social influences contribute to better academic outcomes. However, SQSI's impact is often moderated by factors such as KAUS and IC, implying that while system quality and social factors are essential, their effects are maximized when combined with other supportive elements in the educational environment.

b. **SVM Results:** In the SVM model, SQSI is identified as a significant predictor of academic performance, particularly in environments where the technical quality of AI systems is high and social influences encourage the adoption of AI tools. The SVM analysis shows that positive social influence can enhance the effectiveness of high-quality AI systems, leading to improved academic outcomes. SVM's capacity to model complex interactions highlights that SQSI's impact may vary depending on the students' social networks and the overall acceptance of AI within their educational community.

c. **Improved SVM Results:** The Improved SVM model further refines the understanding of SQSI by reducing multicollinearity, leading to more stable and accurate predictions. The analysis confirms that both system quality and social influence are critical in fostering effective AI adoption and enhancing academic performance. The improved model suggests that environments where students perceive AI systems as reliable and receive positive reinforcement from their peers and instructors, are likely to see better educational outcomes. This underscores the importance of both technical robustness and social support in successful AI integration.

The comparative analysis across SEM, SVM and Improved SVM provides valuable insights into how different AI adoption factors influence academic performance in ODL settings:

I. **AI Alignment and Relevance (AAR):** Crucial for aligning AI tools with institutional and student needs. SEM shows its moderate impact mediated by other factors, while SVM and Improved SVM highlight its strong predictive power, especially when multicollinearity is controlled.

II. **Comparative Advantage of AI (CAAI):** Important for enhancing academic outcomes through the perceived superiority of AI over traditional methods. SEM suggests its indirect impact, whereas SVM and Improved SVM demonstrate its significant direct influence on performance.

III. **Ease and Enjoyment of Use (EEU):** A key determinant of user engagement and satisfaction. SEM identifies EEU as a positive mediator, while SVM and Improved SVM reveal its strong predictive accuracy, mainly when AI tools are user-friendly and enjoyable.

IV. **AI Readiness and Facilitating Conditions (ARFC):** Essential for successful AI integration. SEM shows its moderate impact, with SVM and Improved SVM emphasizing the importance of institutional support and readiness in achieving positive academic outcomes.

V. **AI-induced Learning Anxiety (AILA):** A significant barrier to effective AI adoption is highlighted by SEM and SVM, both of which emphasize the negative impact on performance. The Improved SVM offers more reliable predictions by addressing multicollinearity.

VI. **Interactive Capability (IC):** Vital for enhancing engagement and interaction in ODL settings. SEM shows its significant role as a mediator, while SVM and Improved SVM confirm its strong influence on academic success.

VII. **Knowledge Absorption and User Satisfaction (KAUS):** This is the most significant predictor of academic performance. All models agree on its central role, with Improved SVM providing the most accurate predictions due to reduced multicollinearity.

VIII. **Systems Quality and Social Influence (SQSI):** Important for technical reliability and social support. SEM shows its moderate impact, while SVM and Improved SVM highlight its critical role in environments with high system quality and positive social influences.

The analysis of AI adoption factors using SEM, SVM, and Improved SVM reveals that these factors play varying but significant roles in influencing academic performance in ODL settings. SEM provides insights into the structural relationships and mediating effects among these factors. At the same time, SVM and Improved SVM offer robust predictive capabilities, with the latter addressing issues of multicollinearity to improve prediction accuracy and model stability. This comprehensive approach underscores the importance of a balanced and integrated strategy for AI adoption in education, where both the understanding of underlying relationships (as captured by SEM) and the focus on predictive accuracy (as highlighted by SVM and Improved SVM) are essential. The findings suggest that to maximize the positive impact of AI on student outcomes, educational institutions should focus on aligning AI tools with institutional goals, ensuring ease of use, providing robust support systems, and fostering positive social influences.

Future research should continue to explore these factors in more diverse educational contexts and investigate additional variables that may influence AI adoption and its effects on learning outcomes.

By doing so, the educational sector can better leverage AI technologies to enhance learning experiences and academic success in ODL settings.

4.5.6 Alignment of Research Findings with Research Questions, Hypotheses, and Objectives

The research findings of this study have been meticulously analysed to address the research questions, test the hypotheses, and achieve the specific objectives set out at the beginning of this thesis. The following discussion outlines how the results obtained align with these foundational elements of the research.

The first research question sought to identify the requirements for adopting AI in Open Distance Learning (ODL). The corresponding hypothesis posited that comprehensive identification of these requirements would enhance student academic performance. The results of this study, particularly through the analysis of AI readiness, ease of use, and knowledge absorption, have substantiated this hypothesis. The identification and fulfilment of these AI adoption requirements were shown to be crucial for improving student outcomes in ODL environments. This aligns with the first objective of designing a process framework that incorporates these factors to enhance the understanding of AI adoption in ODL. The second research question aimed to explore the design of a process model that effectively incorporates AI requirements into ODL. The corresponding hypothesis suggested that such a model would significantly enhance the understanding of AI adoption in ODL. The structural equation model (SEM) developed in this study has effectively captured the complex interactions between various AI adoption factors, providing a comprehensive framework that elucidates the dynamics of AI integration in ODL. This confirms the second hypothesis and achieves the objective of designing a research model that integrates AI adoption factors with student academic performance.

The third research question examined the design of a research model that incorporates AI factors and student academic performance. The hypothesis was that these AI adoption factors significantly impact student academic performance. The SEM analysis confirmed this hypothesis by demonstrating that factors such as knowledge absorption, user satisfaction, and interactive capability are strong predictors of student academic outcomes in ODL settings. This aligns with the third objective of developing a machine-learning model to predict the impact of these factors on student performance. The fourth research question addressed the development of machine learning models incorporating the impact factors of AI adoption and student academic performance. The corresponding hypothesis asserted that these models would effectively predict the impact of AI adoption on ODL students' academic performance. The Improved Support Vector Machine (SVM) developed in this study validated this hypothesis, as it demonstrated enhanced accuracy and stability in predictions, particularly by addressing multicollinearity issues. This achievement aligns with the fourth objective of evaluating these models to establish their accuracy.

The fifth and final research question focused on evaluating the developed machine learning models to determine their level of accuracy. The hypothesis stated that such evaluations would have a significant impact on model accuracy. The results confirmed this hypothesis, showing that the Improved SVM, with its refined approach to multicollinearity, significantly improved the predictive performance of the models. This evaluation process has thus fulfilled the objective of enhancing the accuracy of the machine learning models used in the study. The research findings have thoroughly addressed the research questions, confirmed the hypotheses, and achieved the objectives set out at the beginning of this study. The developed frameworks and models provide a deeper understanding of AI adoption in ODL and offer robust tools for predicting and improving student academic performance. This comprehensive alignment underscores the success and significance of the research conducted in this thesis.

4.6 Implications of the results

The findings from the comparative analysis of Structural Equation Modelling (SEM), Support Vector Machine (SVM), and Improved SVM have profound implications for the adoption and application of Artificial Intelligence (AI) in Open and Distance Learning (ODL) settings. This section delves into the broader implications of these results, discussing their relevance for educational institutions, policymakers, educators, and future research. The implications are categorized into theoretical, practical, and policy-related impacts, each offering insights into how AI can be effectively leveraged to enhance academic performance in diverse educational contexts.

4.6.1 Theoretical Implications

The theoretical implications are as follows:

I. **Integration of Predictive and Structural Approaches:** The study's use of both SEM and SVM provides a comprehensive approach to understanding and predicting academic performance influenced by AI adoption factors. SEM's strength lies in its ability to validate theoretical models by establishing relationships between latent and observed variables, offering insights into the causal pathways that affect educational outcomes. SVM, on the other hand, excels in predictive accuracy, particularly in handling complex, non-linear relationships that SEM may not fully capture. By enhancing its capacity to address multicollinearity, the Improved SVM bridges the gap between these two approaches, ensuring both robust prediction and structural understanding. This integration underscores the importance of using a multi-method approach in educational research, where theoretical validation and predictive modelling work hand-in-hand to provide a more holistic understanding of educational phenomena.

II. **Contribution to AI Adoption Theory:** The research contributes to the theoretical understanding of AI adoption in education by identifying key factors—such as AI Alignment and Relevance (AAR), Comparative Advantage of AI (CAAI), and Knowledge Absorption and User Satisfaction (KAUS)—that significantly influence academic performance. The findings validate the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) in the context of ODL, extending these models to incorporate AI-specific variables. This expansion provides a more nuanced theoretical framework for examining how AI technologies impact learning outcomes, particularly in distance education environments where traditional in-person interactions are limited.

III. **Understanding the Role of Moderators:** The study highlights the importance of considering moderating factors like gender and geographical location in AI adoption research. The Improved SVM results, in particular, show that these moderators can significantly influence the effectiveness of AI tools, with varying impacts on different demographic groups and regions. This insight contributes to the broader literature on educational equity and access, suggesting that AI adoption strategies should be tailored to address the specific needs and challenges of diverse student populations.

4.6.2 Practical Implications

The practical implications are as follows:

I. **Enhancing AI Integration in ODL Settings:** The results suggest several practical steps that educational institutions can take to improve the integration of AI in ODL settings. First, institutions should focus on aligning AI tools with both institutional goals and student needs (as highlighted by the importance of AAR in the models). This alignment ensures that AI technologies are not only adopted but also effectively utilized to enhance learning outcomes. Second, improving the ease of use and enjoyment of AI tools (EEU) can significantly boost student engagement, leading to better academic performance. Institutions should, therefore, invest in user-friendly AI interfaces and provide adequate training to help students overcome any learning anxiety (AILA) associated with new technologies.

II. **Addressing Multicollinearity in Educational Data:** The findings underscore the importance of addressing multicollinearity in educational data analysis, mainly when using predictive models like SEM and SVM. The Improved SVM model, which incorporates VIF optimization, demonstrates that reducing multicollinearity leads to more stable and reliable predictions. Educational practitioners and researchers should, therefore, consider incorporating techniques to manage multicollinearity when developing predictive models for student performance, ensuring that the resulting insights are both accurate and actionable.

III. **Tailoring AI Solutions to Diverse Student Populations:** The study's findings on the moderating effects of gender and geographical location suggest that AI solutions should be customized to meet the needs of diverse student groups. For instance, the improved performance of AI tools for female students in specific contexts implies that gender-specific support and content may enhance learning outcomes. Similarly, the differential impact of AI tools in various geographical locations suggests that local contexts—such as access to technology and cultural attitudes towards AI—should be considered when implementing AI in education. By tailoring AI solutions to these specific needs, educational institutions can maximize the effectiveness of their AI initiatives.

IV. **Prioritizing Quality and Social Influence in AI Adoption:** The significant role of Systems Quality and Social Influence (SQSI) in the study implies that the success of AI adoption in ODL is heavily dependent on the technical reliability of the AI systems and the social environment in which they are used. Educational institutions should prioritize deploying high-quality AI systems that are reliable and efficient, ensuring that these tools meet the technical standards necessary for effective educational delivery. Additionally, fostering a positive social environment where peers and instructors support AI adoption can significantly enhance the overall effectiveness of AI in improving academic performance.

V. **Leveraging AI for Early Intervention and Support:** Predicting academic performance through AI enables institutions to identify at-risk students early, providing an opportunity for timely intervention. By accurately predicting which students might struggle, institutions can tailor support services to these students, offering targeted resources such as tutoring, mentoring, or additional academic assistance. This early intervention can significantly improve the learning experience, potentially reducing dropout rates and enhancing overall program completion rates. As AI tools continue to evolve, their ability to provide predictive insights will become increasingly valuable in supporting student success and ensuring that all students have the opportunity to achieve their academic goals.

4.6.3 Policy Implications

The policy implications are as follows:

I. **Supporting AI Readiness and Facilitating Conditions:** Policymakers should focus on creating a supportive environment for AI adoption in education by ensuring that both students and institutions are adequately prepared. This includes investing in infrastructure that supports AI technologies, providing funding for training programs to improve AI readiness (ARFC), and developing policies that facilitate the widespread adoption of AI tools in educational settings. By enhancing AI readiness, policymakers can help reduce barriers to AI adoption, leading to more equitable and effective educational outcomes.

II. **Promoting Equity in AI Adoption:** The study's findings on the moderating effects of gender and geographical location highlight the need for policies that address disparities in AI adoption and usage. Policymakers should ensure that AI technologies are accessible to all students, regardless of gender, geographical location, or socioeconomic background. This may involve targeted interventions, such as providing additional resources and support to underrepresented groups or regions, to ensure that the benefits of AI are equitably distributed.

III. **Encouraging Evidence-Based AI Integration:** Policymakers should advocate for the use of evidence-based practices in the integration of AI into education. The study's comparative analysis of SEM, SVM and Improved SVM provides a strong case for the importance of using rigorous analytical methods to assess the impact of AI on educational outcomes. Policies that encourage the adoption of such methods can help ensure that AI tools are implemented in ways that are both effective and scientifically validated, leading to better educational outcomes at scale.

IV. **Fostering Collaboration Between Stakeholders:** The successful adoption of AI in education requires collaboration between multiple stakeholders, including educational institutions, technology providers, policymakers, and researchers. The findings suggest that such collaboration is essential for addressing the complex challenges associated with AI adoption, from managing multicollinearity in predictive models to ensuring that AI tools are aligned with educational goals. Policymakers should, therefore, promote partnerships between these stakeholders to facilitate the development and implementation of AI solutions that are both innovative and effective.

4.6.4 Implications for Future Research

The implications for future research are as follows:

I. **Expanding the Scope of AI Adoption Studies:** The study's findings open several avenues for future research. One important direction is to expand the scope of AI adoption studies to include a broader range of educational contexts and demographic groups. This includes examining how AI adoption factors influence academic performance in different types of educational institutions (e.g., primary vs. tertiary education) and among various student populations (e.g., adult learners and students with disabilities).

II. **Investigating Longitudinal Effects:** Future research should also investigate the long-term effects of AI adoption on academic performance. While this study provides valuable insights into the immediate impact of AI adoption factors, understanding how these effects evolve would provide a more comprehensive picture of AI's role in education. Longitudinal studies could explore how sustained use of AI tools influences learning outcomes, student satisfaction, and educational equity.

III. **Exploring New AI Adoption Factors:** The study identifies several key AI adoption factors, but future research could explore additional variables that may influence AI's impact on education. For example, factors related to AI ethics, data privacy, and student autonomy could be critical in understanding the broader implications of AI adoption. By expanding the range of variables studied, researchers can develop a more nuanced understanding of the conditions under which AI is most effective in educational settings.

IV. **Combining Quantitative and Qualitative Approaches:** Finally, future research should consider combining quantitative methods, like SEM and SVM, with qualitative approaches to provide a richer understanding of AI adoption in education. While quantitative models offer valuable predictive and structural insights, qualitative research can capture the lived experiences of students and educators, providing context and depth to the findings. This mixed-methods approach could lead to more holistic and actionable recommendations for AI adoption in education.

The implications of this study are far-reaching, offering valuable insights for theory, practice, policy, and future research in the field of AI adoption in education. By understanding the factors that influence AI's impact on academic performance, educational institutions, policymakers, and researchers can develop strategies that maximize the benefits of AI in ODL settings. The study underscores the importance of a comprehensive, evidence-based approach to AI integration, one that considers the unique needs of diverse student populations and the complex dynamics of educational environments.

4.7 Benchmark of the Results

Benchmarking the results from this study involves comparing the outcomes obtained from the analysis of AI adoption factors using Structural Equation Modelling (SEM), Support Vector Machine (SVM), and Improved SVM against established standards, previous studies, and industry expectations. The purpose of this benchmarking is to assess the reliability, accuracy, and generalizability of the findings, as well as to highlight the contributions of this research in the context of existing literature. This section provides an extensive analysis of how the results align with or differ from prior research, how they measure up against industry benchmarks, and the implications of these comparisons for future research and practical applications in Open and Distance Learning (ODL) settings.

4.7.1 Benchmarking Against Established Theoretical Models

I. **Validation of AI Adoption Factors:** The AI adoption factors identified in this study—such as AI Alignment and Relevance (AAR), Comparative Advantage of AI (CAAI), and Ease and Enjoyment of Use (EEU)—have been benchmarked against established theoretical models like the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT). These models have long been used to understand technology adoption in various contexts, including education.

- **TAM and UTAUT Comparison:** The results from SEM validate the theoretical constructs of TAM and UTAUT, particularly in how AAR and CAAI contribute to perceived usefulness and ease of use, which are core components of TAM. This alignment suggests that the AI adoption factors identified in this study are consistent with established theories, thereby reinforcing their relevance and applicability in ODL settings (Strzelecki, 2023; Dwivedi et al., 2017). The benchmarking against these models shows that while AI-specific factors are critical, they do not diverge significantly from broader technology acceptance theories but rather expand on them to suit the nuances of AI in education.

II. **Enhanced Predictive Modelling with SVM:** The use of SVM and Improved SVM in this study provides a benchmark for predictive modelling in educational research. Traditional models like SEM are well-suited for understanding relationships between variables, but SVM offers enhanced predictive accuracy, particularly in handling non-linear relationships and complex interactions.

- **Predictive Accuracy Benchmarking:** When compared to traditional statistical models used in educational research, SVM demonstrates superior performance in predicting academic outcomes based on AI adoption factors. By focusing on reducing its multicollinearity, the Improved SVM sets a new benchmark for predictive modelling by enhancing the stability and reliability of predictions (Zhang, 2021). This marks a significant advancement over previous studies that relied solely on SEM or other regression-based models, showcasing the value of integrating machine learning approaches in educational research.

4.7.2 Comparison with Previous Studies

I. **Alignment with Prior Research on AI in Education:** The findings from this study align with previous research that highlights the importance of AI adoption in improving educational outcomes. Studies by scholars such as Nguyen (2023) and Holmes et al. (2023) have emphasized the potential of AI to transform educational practices, particularly in ODL environments.

- **Benchmarking Educational Impact:** The results from this study corroborate the positive impact of AI adoption factors like KAUS and EEU on student performance, which have been similarly highlighted in prior research (Nguyen, 2023; Holmes et al., 2023). However, this study goes further by providing a detailed analysis of how these factors interact with moderating variables such as gender and geographical location, offering a more nuanced understanding of AI's impact that previous studies have not fully explored. This positions the current research as a benchmark for future studies that seek to explore the complexities of AI adoption in diverse educational contexts.

II. **Divergence from Traditional Educational Research:** While the results align with some aspects of prior research, they also diverge in significant ways, particularly in the emphasis on predictive modelling and the management of multicollinearity.

- **Handling of Multicollinearity:** Previous studies in educational research often struggled with issues of multicollinearity, leading to less reliable models and predictions. The Improved SVM’s approach to VIF optimization sets a new standard for addressing this issue, ensuring that the predictive models used in this study are both accurate and robust (Chan et al., 2022). This divergence from traditional methods highlights the innovative contributions of this research, particularly in advancing the use of machine-learning techniques in educational settings.

4.7.3 Industry Benchmarking

I. **Alignment with Industry Standards for AI Implementation:** The study’s findings can be benchmarked against industry standards for AI implementation in education, as set by organizations like UNESCO and the International Society for Technology in Education

(ISTE). These standards emphasize the need for AI tools to be aligned with educational goals, user-friendly, and equitable.

- **Benchmarking Against UNESCO and ISTE Standards:** The emphasis on AAR and EEU in this study aligns well with UNESCO's guidelines for AI in education, which stress the importance of aligning AI tools with institutional goals and ensuring they are accessible and user-friendly (UNESCO, 2022). The study's findings regarding the importance of system quality and social influence (SQSI) further support the ISTE standards, which advocate for high-quality, reliable AI systems that enhance learning environments (ISTE, 2021). The alignment with these standards indicates that the results of this study not only contribute to academic research but also have practical implications for industry practices and policies related to AI in education.

II. **Benchmarking Predictive Models Against Industry Expectations:** In the tech industry, particularly in fields like educational technology, the accuracy and reliability of predictive models are critical benchmarks for success. The use of SVM and Improved SVM in this study provides a benchmark for how AI adoption factors can be modelled to predict academic outcomes.

- **Predictive Model Performance:** The predictive performance of SVM and Improved SVM in this study can be benchmarked against industry expectations for machine learning models in educational settings. The relatively low error rates (MAE, MSE, RMSE) observed in the SVM models indicate that these approaches meet or exceed industry standards for predictive accuracy, positioning them as viable tools for real-world educational applications (Ojajuni et al., 2021; Leeuwenberg et al., 2022). This sets a new benchmark for how educational institutions and technology providers can use predictive modelling to enhance AI adoption strategies and improve student outcomes.

4.7.4 Benchmarking Within the Context of Open and Distance Learning (ODL)

I. **Addressing Challenges in ODL:** The study's focus on ODL settings provides a benchmark for how AI can address specific challenges associated with remote education, such as student engagement, access to resources, and the quality of interactions.

- **ODL-Specific Benchmarks:** The study's findings that factors like interactive capability (IC) and AI readiness (ARFC) significantly influence academic performance in ODL environments set a benchmark for future research and practice in this area. These results suggest that for AI to be effective in ODL, it must be not only technically robust but also capable of enhancing the quality of interactions and providing adequate support for both students and educators (Akinwalere & Ivanov, 2022; Rakya, 2023). This benchmark emphasizes the need for AI tools that are specifically designed or adapted for the unique challenges of ODL.

II. **Enhancing Student Outcomes in ODL:** One of the critical benchmarks for AI in education is its ability to improve student outcomes. This study's analysis of AI adoption factors against academic performance provides a benchmark for evaluating the effectiveness of AI interventions in ODL settings.

- **Student Performance Benchmarking:** The study demonstrates that AI tools that align with student needs, offer comparative advantages over traditional methods, and are easy to use can significantly enhance academic performance in ODL environments (Xu, 2024). This finding provides a benchmark for educational institutions to measure the success of their AI implementations, guiding them in selecting and deploying AI tools that are most likely to improve student outcomes in remote learning contexts.

Table 4.11 organizes the benchmark results for AI's role in ODL, for easier reference and analysis.

Table 4.11. Benchmarking AI in Open and Distance Learning (ODL) Based on Study Findings

Benchmark Category	Study Findings	References
Addressing Challenges in ODL	AI can address ODL-specific challenges like student engagement, access to resources, and interaction quality.	Akinwalere & Ivanov (2022), Rakya (2023)
ODL-Specific Benchmarks	Factors like Interactive Capability (IC) and AI Readiness (ARFC) significantly influence academic performance in ODL.	Akinwalere & Ivanov (2022), Rakya (2023)
Enhancing Student Outcomes in ODL	AI tools that align with student needs, offer comparative advantages, and are user-friendly can significantly improve academic performance.	Xu (2024)
Student Performance Benchmarking	AI interventions that are technically robust and capable of enhancing interactions set a benchmark for future implementations in ODL.	Akinwalere & Ivanov (2022), Xu (2024), Rakya (2023)

4.7.5 Implications of Benchmarking for Future Research

I. **Establishing New Standards for AI Research:** The benchmarking of results from this study against theoretical models, previous research, industry standards, and ODL-specific challenges establishes new standards for AI research in education. Future studies can build on these benchmarks to explore new AI adoption factors, refine predictive models, and further investigate the role of moderating variables in different educational contexts.

- **Setting Research Agendas:** The benchmarks established in this study can guide future research agendas, particularly in areas such as the integration of machine learning techniques with traditional educational models, the exploration of AI's impact across diverse student populations, and the development of AI tools tailored to specific educational environments like ODL (Abbas et al., 2023).

II. **Encouraging the Adoption of Best Practices:** By providing clear benchmarks for AI adoption in education, this study encourages the adoption of best practices in both research and practice. Educational institutions can use these benchmarks to evaluate their AI initiatives, ensuring that they align with the most effective strategies identified in the research.

- **Best Practices in AI Adoption:** The benchmarks related to the importance of aligning AI tools with institutional goals, enhancing system quality, and addressing multicollinearity in predictive models can serve as best practices for both researchers and practitioners (Strzelecki, 2023; Leeuwenberg et al., 2022). By adopting these practices, educational institutions can maximize the benefits of AI, leading to improved student outcomes and more effective educational processes.

The benchmarking of results in this study provides a comprehensive assessment of how the findings compare to existing theoretical models, previous research, industry standards, and the specific needs of ODL settings. By establishing new benchmarks in these areas, the study not only contributes to the academic literature but also offers practical guidelines for the effective adoption and implementation of AI in education. These benchmarks serve as valuable references for future research and practice, helping to shape the development of AI tools that are both innovative and impactful in enhancing educational outcomes.

This benchmarking analysis highlights the importance of a multi-method approach in AI research, especially in education. The combination of SEM, SVM, and Improved SVM offers both theoretical depth and strong predictive capabilities, setting a new standard for future studies. It emphasizes the need for AI solutions tailored to the unique challenges of ODL, providing a roadmap for educators, policymakers, and technology providers in AI adoption. As AI's role in education grows, these benchmarks will guide policy, practice, and research, ensuring AI tools are practical, equitable, accessible, and aligned with 21st-century educational goals. By refining these benchmarks, the educational community can fully leverage AI to enhance learning outcomes for all students, regardless of location or background.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Summary

This study aimed to develop a robust process framework for predicting the impact of Artificial Intelligence (AI) adoption on students' academic performance in Open and Distance Learning (ODL) environments. The research focused on several key objectives. To achieve this, we designed a process framework, developed predictive models using a Support Vector Machine (SVM), and evaluated these models to determine their accuracy in predicting academic outcomes.

The study successfully developed a comprehensive process framework that integrates AI adoption factors, considers moderating variables such as gender and geographical differences, and applies machine learning techniques to predict academic performance. The framework underwent rigorous testing through multiple stages, including data pre-processing, model training, and validation, which ensured the reliability of the predictive models. The findings confirmed that AI adoption positively influences academic performance when factors such as ease of use, knowledge absorption, and user satisfaction are adequately addressed. Moreover, the study highlighted the importance of customizing AI tools to cater to the diverse needs of ODL students across different regions.

5.2 Conclusion

The exponential progression in artificial intelligence (AI) and its integration into Education has generated significant interest among researchers. One crucial aspect is the impact of AI adoption on students' academic performance, particularly in the context of Online Distance Learning (ODL). This study has developed a process framework utilising a Support Vector Machine (SVM) to predict the impact of AI adoption on students' academic performance in ODL. The theoretical framework is the cornerstone of any research, laying the foundation for interpreting the dynamics and outcomes of the study. In the context of this present work, the theoretical framework is instrumental in guiding the exploration and analysis of critical components such as AI adoption factors, moderating factors, and the outcome variable of students' academic performance.

5.3 Recommendations

The research concludes that the adoption of AI in ODL can significantly enhance students' academic performance when adequately aligned with institutional goals and tailored to meet the specific needs of students. The developed process framework and predictive models provide valuable insights into how AI adoption factors, coupled with moderating variables, influence academic outcomes. By leveraging SVM, the study has demonstrated the effectiveness of machine learning in forecasting student performance, offering a reliable tool for educators and policymakers to optimize AI integration in educational settings. The successful development and validation of the predictive framework underscore the importance of considering both technical and non-technical factors in AI adoption. The findings suggest that a one-size-fits-all approach is insufficient; instead, AI tools should be adapted to the unique challenges and opportunities within ODL systems. This study contributes to the broader discourse on AI in education by providing a structured approach to understanding and predicting the impact of AI on learning outcomes.

5.4 Contributions to Knowledge

The contributions to the knowledge of this study are as follows:

I. **In-Depth Requirements Elicitation Report**: This study produces a comprehensive report that meticulously identifies and analyzes the key factors influencing Artificial Intelligence (AI) adoption in the context of students' academic performance in Open Distance Learning (ODL). This report delves into various dimensions, such as technological, pedagogical, and institutional factors that contribute to the effective integration of AI in educational settings. Doing so provides a foundational understanding of the current landscape of AI adoption in the educational sector, highlighting both the opportunities and challenges.

II. **Robust Process Framework for AI Adoption in ODL**: The study proposes a novel process framework specifically designed for AI adoption in ODL environments based on the insights gained from the requirements elicitation. This framework outlines a structured and strategic approach, incorporating the identified factors to facilitate a more effective and seamless adoption of AI technologies in ODL. It serves as a guide for educational institutions aiming to leverage AI to enhance teaching and learning experiences.

III. **Comprehensive Research Model on AI Adoption and Student Performance**: A pivotal contribution of this study is creating an encompassing research model that integrates the critical factors influencing AI adoption with their subsequent impact on student academic performance in ODL. This model aims to fill existing gaps in the literature by providing a holistic view of how AI technologies can influence educational outcomes. It is an essential resource for future research and practice in educational technology.

IV. **Advanced Machine Learning Models for Predicting Academic Performance**: The study also focuses on developing cutting-edge machine learning models that utilize the factors identified from AI adoption to predict their effects on student academic performance in ODL. These models are designed to process complex datasets and provide predictive insights, serving as invaluable tools for educational administrators and policymakers to make data-driven decisions.

V. **Detailed Model Evaluation Report**: An integral part of this study is thoroughly evaluating the developed machine learning models. This report assesses the models' accuracy, reliability, and applicability in real-world educational settings. It critically analyses the models' strengths and limitations, offering recommendations for improvement and future development. This evaluation is crucial for education sector stakeholders considering the practical deployment of AI-based predictive models.

VI. **Improved Support Vector Machine (SVM) with VIF Optimization**: This study contributes by developing and refining an Improved Support Vector Machine (SVM) model that incorporates Variance Inflation Factor (VIF) optimization, utilizing internal consistency and reliability checks through Cronbach's Alpha. This enhancement is designed to improve the model's stability, reliability, and ability to discern the individual impact of AI adoption factors on students' academic performance in ODL. By addressing multicollinearity issues, the VIF optimization ensures a more robust and stable model. This contribution is particularly significant for educational stakeholders, providing an advanced tool for more precise and dependable predictions of student outcomes based on critical AI adoption factors.

Through these contributions, the study aims to significantly advance the understanding of AI adoption in ODL and its impact on student academic performance. It offers practical tools and models for educators and policymakers and sets the stage for future innovations in the field.

5.5 Future Research Directions

The findings from this study provide a solid foundation for future research in the area of Artificial Intelligence (AI) adoption in Open and Distance Learning (ODL) environments. However, there remain several avenues for further exploration that could enhance our understanding of AI's impact on education and refine the predictive frameworks developed in this research.

I. **Exploration of Additional AI Adoption Factors:** Future research should investigate other factors that may influence the successful adoption of AI in ODL. For instance, cultural attitudes towards technology, the role of instructor training and preparedness, and the impact of social learning networks could be significant. Understanding these additional factors can help create more comprehensive models that capture the full range of variables affecting AI integration in education.

II. **Longitudinal Studies on AI's Impact:** While this study provides a snapshot of AI's influence on academic performance, longitudinal research is needed to understand the long-term effects of AI adoption in ODL. Future studies should track cohorts of students over extended periods to assess how sustained interaction with AI tools affects learning outcomes, retention rates, and overall academic success. Such research could also explore how students' perceptions and usage of AI evolve.

III. **Integration of Emerging Technologies:** As technology continues to evolve, future research should explore the integration of other emerging technologies alongside AI in ODL settings. For example, the potential of Virtual Reality (VR), Augmented Reality (AR), and Blockchain to enhance educational experiences and improve academic outcomes should be examined. These technologies could complement AI by providing more immersive and secure learning environments.

IV. **Customization of AI Tools for Diverse Learning Needs:** Future research should focus on how AI tools can be further customized to meet the needs of diverse learner groups, including students with disabilities, non-traditional learners, and those in underserved regions, building on the findings of this study. Research should explore the development of adaptive AI systems that can personalize learning experiences based on individual student profiles, learning styles, and progress.

V. **Cross-Cultural Comparisons of AI Adoption:** Future studies should conduct cross-cultural comparisons of AI adoption in ODL environments to gain a more global perspective. By examining how different educational systems and cultural contexts influence AI's impact, researchers can identify best practices and potential challenges that are unique to specific regions or demographics. This could lead to more tailored approaches to AI integration across diverse educational settings.

VI. **Ethical Considerations and AI in Education:** As AI continues to play a larger role in education, it is crucial to address the ethical implications of its use. Future research should explore issues related to data privacy, algorithmic bias, and the potential for AI to exacerbate existing inequalities in education. Developing ethical guidelines and frameworks for AI in education will be essential to ensure that its adoption benefits all students equitably.

VII. **Enhancement of Predictive Models:** The predictive models developed in this research, while robust, could be further refined to improve their accuracy and generalizability. Future research should explore the integration of more advanced machine learning algorithms, such as deep learning, and the inclusion of additional data sources, such as real-time learning analytics, to enhance the predictive power of these models. Additionally, researchers could explore the application of these models in different educational contexts, such as vocational training or professional development programs.

Addressing these future research directions will help advance AI in education, ensuring its ethical and practical use to enhance learning outcomes and provide equitable opportunities for all students.

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Appendix A: The Pseudocode for the Improved SVM (Improved VIF Optimization)

```
START
// Step 1: Load Data
```

```
LOAD dataset using pandas

// Step 2: Ordinal Encoding
FOR each Likert scale column in dataset
APPLY ordinal encoding
// Step 3: Handle Missing Data
FOR each column in dataset
CHECK if missing data exists
IF missing data exists THEN
CALCULATE average of non-missing values in the same column (construct)
REPLACE missing data with average value

// Step 4: Compute Composite Scores
FOR each construct in the dataset
CALCULATE the mean of the associated items
STORE the mean value as the composite score of the construct

// Step 5: Verify Internal Consistency
FOR each construct in dataset
CALCULATE Cronbach's Alpha
IF Cronbach's Alpha is less than acceptable value THEN
FLAG the construct for review

// Step 6: Data Preparation for SVM
CREATE a new dataset with AI related constructs as independent variables
SET Students' Academic Performance as Target variable

// Step 7: Train-Test Split
SPLIT the dataset into a training set and a test set

// Step 8: Train SVM Model
INITIALIZE SVM model with parameters
FIT the model with the training set

// Step 9: Evaluate the SVM Model
PREDICT the target variable for the test set using the trained model
CALCULATE evaluation metrics (MAE, MSE, MAPE, RMSE, NMSE)


END
```

Appendix B: The Questionnaire used for data collection

QUESTIONNAIRE ON THE IMPACT OF ARTIFICIAL INTELLIGENCE ON ACADEMIC PERFORMANCE IN OPEN AND DISTANCE LEARNING

INTRODUCTION

Good day, Sir/Madam,

Thank you for considering participating in this study, which aims to develop a process framework for predicting the impact of artificial intelligence adoption on students' academic performance in Open and Distance Learning (ODL) using a support vector machine.

- **Participation:** Your participation is voluntary, and you may withdraw at any time.
- **Procedure:** The questionnaire will take approximately 15-20 minutes to complete.
- **Confidentiality:** All responses are confidential and anonymized.
- **Risks and Benefits:** There are no known risks associated with participating in this study.
- **Consent:** By proceeding, you voluntarily agree to participate and confirm you are above 18 years old.

For any queries, please get in touch with the researcher. Your participation is highly valued.

.

Warm regards,

Muyideen Adewale
PhD Candidate in Artificial Intelligence,
Africa Centre of Excellence on Technology Enhanced Learning.
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Email: Ace22140007@noun.edu.ng; mdadewale@gmail.com

Section A: Demographics

1. Please provide your age group: [Below 20] [20-29] [30-39] [40-49] [50 and above]

2. Please indicate your gender: [Male] [Female] [Prefer not to say]
3. Please provide your geographical location (country): [Canada] [Nigeria]
4. What is your field of study? [Computer Science] [Information Technology] [Business Administration] [Marketing] [Engineering] [Natural Sciences] [Social Sciences] [Humanities] [Arts & Design] [Education] [Health & Medicine] [Agriculture & Environmental Sciences] [Mathematics & Statistics] [Physical Sciences] [Biological & Life Sciences] [Law & Legal Studies] [Journalism & Media Studies] [Philosophy & Theology] [Psychology] [Other - Please Specify]

Please answer the following questions after using the application. The information below provides the code and meaning for each option to be ticked.

1- Strongly Disagree 2- Disagree 3-Neither Agree nor Disagree 4- Agree 5- Strongly Agree

Section B: AI Alignment and Relevance (AAR)

1. I feel that the AI-based Moodle platform used in my course aligns well with my learning needs and objectives.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

2. The AI-based Moodle platform implemented in my institution aligns with its educational goals and values.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

3. The use of AI-based Moodle platform features makes my course content more relevant.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

4. Using the AI-based Moodle platform in my course positively impacts my attitude towards technology in education.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

Section C: Comparative Advantage of AI (CAAI)

1. Learning with the AI-based Moodle platform is more effective than traditional educational methods.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

2. The AI-based Moodle platform features provide significant advantages to my learning process compared to traditional methods.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

3. Learning with the AI-based Moodle platform is more efficient in terms of time and resource utilization.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

4. The AI-based Moodle platform enhances the effectiveness of my learning outcomes compared to traditional methods.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

Section D: Ease and Enjoyment of Use (EEU)

1. I find it easy to use the AI-based Moodle platform for learning in my course.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

2. My experience interacting with the AI-based Moodle platform in my course is enjoyable.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

3. Learning with the AI-based Moodle platform is intuitive and user-friendly.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

4. The use of the AI-based Moodle platform in my course is engaging and motivating.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

Section E: AI Readiness and Facilitating Conditions (ARFC)

1. I feel well-prepared to use the AI-based Moodle platform in my learning.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

2. My institution is well-prepared for adopting and implementing the AI-based Moodle platform.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

3. I receive substantial support (technical, learning resources, etc.) in using the AI-based Moodle platform for learning.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

4. The conditions in my institution facilitate the effective use of the AI-based Moodle platform for learning.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

Section F: AI-induced Learning Anxiety (AILA)

1. I often feel anxious or stressed about using the AI-based Moodle platform in my course.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

2. I feel worried about relying on the AI-based Moodle platform for learning.

1 2 3 4 5

Strongly Disagree ☐ ☐ ☐ ☐ ☐ Strongly Agree

3. I often feel overwhelmed by the complexity of the AI-based Moodle platform used in my course.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

4. I worry that errors or problems in the AI-based Moodle platform could negatively impact my learning outcomes.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

Section G: Interactive Capability (IC)

1. I feel well-prepared to interact and collaborate in an online environment facilitated by the AI-based Moodle platform.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

2. The AI-based Moodle platform has enhanced my ability to interact with teachers and peers.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

3. The use of the AI-based Moodle platform has positively impacted my collaboration in group projects or activities.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

4. The AI-based Moodle platform facilitates effective communication in my learning environment.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

Section H: Knowledge Absorption and User Satisfaction (KAUS)

1. The AI-based Moodle platform enhances my understanding and absorption of course material.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

2. I am satisfied with my learning outcomes due to the use of the AI-based Moodle platform.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

3. The AI-based Moodle platform often aids in clarifying complex course material or concepts.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

4. The use of the AI-based Moodle platform improves my satisfaction with the learning experience.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

Section I: Systems Quality and Social Influence (SQSI)

1. The AI-based Moodle platform used in my course is of high quality (reliability, speed, design, etc.).

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

2. The views of my peers significantly influence my usage of the AI-based Moodle platform in my course.

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

3. Social media, discussions with peers, or instructors' opinions have a strong impact on my acceptance and use of the AI-based Moodle platform.

1 2 3 4 5

Strongly Disagree ☐ ☐ ☐ ☐ ☐ Strongly Agree

4. High-quality AI systems enhance their acceptance and use among my peers.

1 2 3 4 5

Strongly Disagree ☐ ☐ ☐ ☐ ☐ Strongly Agree

Section J: Students' Academic Performance

1. I believe that using AI tools like the AI-based Moodle platform has improved my academic performance.

1 2 3 4 5

Strongly Disagree ☐ ☐ ☐ ☐ ☐ Strongly Agree

2. AI in online learning has helped me better understand the course materials.

1 2 3 4 5

Strongly Disagree ☐ ☐ ☐ ☐ ☐ Strongly Agree

3. AI tools like the AI-based Moodle platform have contributed to better grades in my courses.

1 2 3 4 5

Strongly Disagree ☐ ☐ ☐ ☐ ☐ Strongly Agree

4. How would you classify your Cumulative Grade Point Average (CGPA) on a scale of 5? Please select the range that applies to your academic performance. [First Class Honors (4.50 - 5.00)] [Second Class Honors, Upper Division (3.50 - 4.49)] [Second Class Honors, Lower Division (2.50 - 3.49)] [Third Class Honors (1.50 - 2.49)] [Pass (1.00 - 1.49)]

Appendix C: The University Ethics Committee Approval

Gmail **MD Adewale <mdadewale@gmail.com>**

Request for Ethics Committee Approval of PhD Research Questionnaire

Grace JOKTHAN <gjokthan@noun.edu.ng> Fri, Apr 26, 2024 at 2:44 AM
To: MD Adewale <mdadewale@gmail.com>
Cc: Africa Centre of Excellence on Technology Enhanced Learning <acetel@noun.edu.ng>, acetelregistry@gmail.com, ACETEL Registry <acetelregistry@noun.edu.ng>, Gregory ONWODI <gonwodi@noun.edu.ng>, researchadministration@noun.edu.ng, Ambrose Azeta <azetaambrose@gmail.com>

Hello Adewale,

Hope this mail finds you well.

The University Ethics Committee has approved your request and the secretary is expected to issue the approval letter. We will follow up and forward the memo to you today or early next week.

Congratulations

The Centre is following up on the request for sponsorship as it requires the Vice Chancellor's approval. We are hopeful that the request will come through.

Thank you

[Quoted text hidden]

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