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Factors Influencing the Acceptance of ChatGPT Usage Among Higher Education Students in Bangkok, Thailand

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ABSTRACT

Objective: Utilising perceived ease of use and perceived usefulness of the Technology Acceptance Model (TAM), considering facilitating conditions, attitude, as well as privacy and security factors, this study endeavours to dissect the determinants influencing the acceptance of ChatGPT usage among higher education students in Bangkok, Thailand.

Methodology: Employing a quantitative methodology, the research conducted questionnaires as its primary means of data collection from a sample of 400 higher education students in Bangkok, Thailand, through convenience sampling. The hypotheses were tested, and data analysis was conducted using analytical software and statistical methods for examination.

Result: The utilisation of ChatGPT among higher education students was notably impacted by facilitating conditions and attitude, whereas perceived ease of use, perceived usefulness, and concerns pertaining to privacy and security did not exhibit significant influence.

Conclusion: This study highlights the importance of attitudes and facilitating conditions in influencing ChatGPT adoption among higher education students in Bangkok, Thailand. However, perceived ease of use, perceived usefulness, as well as privacy and security considerations did not directly impact usage.

Recommendation: The study highlights the complexity of technology adoption in education and the importance of addressing diverse factors for successful implementation. Executives, educational leaders, and other stakeholders should consider these factors when integrating ChatGPT and other educational technologies. Policymakers may need to establish guidelines addressing privacy and security concerns, while academic institutions should incorporate user experience, practicality, and security into their technology strategies.

Keywords: *Perceived Ease of Use and Perceived Usefulness of the TAM, Facilitating Conditions, Attitude, Privacy and Security factors, ChatGPT Usage, Higher Education*

INTRODUCTION

In the era of digital technology, the adoption of artificial intelligence (AI) is imperative. Since its inception, AI has presented numerous opportunities and challenges across various industries. Likewise, AI must be taken into account when driving innovation in a global economy. Numerous AI-powered technologies have been developed, all with the potential to enhance the economy by elevating the quality of life for people (Limna, 2023). The Chat Generative Pre-Trained Transformer (ChatGPT) is an innovative creation developed by OpenAI, serving as a powerful artificial intelligence (AI) tool designed to generate text-based responses based on user inputs. What sets it apart is its ability to understand the nuances of natural language and provide coherent and contextually relevant responses to a wide range of user queries. Since its launch in November 2022, ChatGPT has experienced rapid growth, accumulating an impressive user base of 100 million in just two months. In response to this overwhelming interest, OpenAI has introduced a subscription plan priced at $20 per month, which grants users unrestricted access to ChatGPT, particularly during periods of high demand. This subscription also offers faster response times, making it more practical for various applications (Jangjarat et al., 2023; Klayklung et al., 2023; Limna et al., 2023).

ChatGPT has emerged as a groundbreaking development in the field of education technology, especially in the realm of conversational AI integration. This AI model, built on a foundation of extensive language training, possesses the remarkable ability to understand natural language and context. Its potential in education is multifaceted, as it can provide personalised learning experiences for students. It achieves this by dynamically adjusting the difficulty level of learning materials based on individual student progress. Additionally, ChatGPT can offer immediate feedback on students' work and streamline administrative tasks such as grading and record-keeping (Rasul et al., 2023; Sullivan, Kelly, & McLaughlan, 2023). Beyond the traditional classroom setting, ChatGPT extends its reach to remote learning environments, offering students valuable access to educational resources and support outside the physical confines of a school or university. Its adaptability and versatility position it as a transformative force in education technology, poised to enhance the learning experiences of students across various educational contexts (Bahroun et al., 2023; Klayklung et al., 2023).

Attitudes toward technology, as indicated by Martínez et al. (2020), encompass preexisting beliefs and perceptions that can influence the teaching-learning process and impact the academic and professional performance of students, particularly those who rely on technology as a tool for their studies. According to Woodenson (2022), the prevailing trend in education involves the integration of technology into the learning process. With an increasing number of teachers utilising information technology to enhance instruction, more researchers are delving into the realm of technology-integrated education. In 1986, Davis introduced the Technology Acceptance Model (TAM), asserting that a technology's ease of use and usefulness significantly impact users' intentions to use it. In this context, behavioural intention refers to an individual's conscious plans or the likelihood of engaging or refraining from specific behaviours. By leveraging the TAM model, researchers can anticipate users' readiness to embrace technology based on their perceptions. Furthermore, as indicated by Limna et al. (2022), facilitating conditions is a crucial determinant within the Unified Theory of Acceptance and Use of Technology (UTAUT) framework. In this context, facilitating conditions refer to an individual's belief in the presence of an organisational and technical infrastructure that supports the use of technology. The greater the ease of access to technology, the more proficient individuals become in its utilisation, thereby resulting in a higher rate of adoption among technology users. Likewise, when individuals are provided with more facilitating conditions for technology usage, they tend to engage with it more frequently. Over the past decade, the adoption of technology in educational settings has ushered in a data-driven approach to decision-making within organisations. This shift has brought about positive changes in the field of learning. However, it also introduces challenges and threats that must be addressed, particularly concerning the safeguarding of protection, privacy, and confidentiality across all academic roles (Amo et al., 2021).

Considering their importance, it is of paramount importance to investigate individuals' intentions to embrace and employ technology, utilising perceived ease of use and perceived usefulness of the TAM, considering facilitating conditions, attitude, as well as privacy and security factors. These conceptual frameworks serve as invaluable tools for both researchers and organisations, facilitating the comprehension and prediction of technology adoption. They also play a pivotal role in crafting effective strategies for the successful implementation of technology. Hence, employing these frameworks, this study endeavours to dissect the determinants influencing the acceptance of ChatGPT usage among higher education students in Bangkok. This research holds significance in its pursuit to gain insights into how students within a specific geographical context perceive and adopt technology within the realm of education. Such understanding can potentially contribute to the advancement and seamless integration of technology into educational practices.

LITERATURE REVIEW

ChatGPT, a creation of OpenAI, represents a significant leap in the field of natural language processing (NLP). While the original GPT architecture was designed for tasks such as machine translation and summarization, ChatGPT takes a different approach. Instead of being primarily geared towards predictive tasks, it functions as a generative AI, capable of spontaneously crafting fresh content during real-time conversations. What sets ChatGPT apart is its role as a text-to-text generative AI, distinguishing it from models like OpenAI's DALL-E, which focuses on generating images from textual descriptions. A notable strength of ChatGPT is its ability to maintain a consistent persona or identity throughout a conversation, ensuring more genuine and coherent dialogues rather than disjointed responses. This capability is a result of extensive training on a diverse dataset encompassing various forms of conversational text, including chat logs, forum discussions, and social media interactions. Thanks to this rigorous training and its unique architecture, ChatGPT has the remarkable capacity to generate responses that closely mimic human language, making it an adaptable tool with diverse applications across multiple domains. Remarkably, within just one week of its initial public release on November 30, 2022, ChatGPT garnered over one million subscribers, leaving the world astounded by its extraordinary capabilities. Its potential to tackle complex tasks in the education sector has sparked a range of reactions among educators, as it hints at the possibility of a significant transformation in established educational practices (Klayklung et al., 2023; Su & Liu, 2023).

As stated by Martínez et al. (2020), in a broad context, attitudes can be defined as individuals' positive or negative sentiments regarding a specific subject. These attitudes are predispositions that are acquired and can evolve throughout a person's life. Some authors assert that attitudes are not inherent but can be altered to foster more appropriate perspectives (Binder & Niederle, 2006). According to Ayub (2017), attitudes represent an individual's opinions about things, people, or particular issues. These attitudes can range from being positive, negative, neutral, or may vary depending on the situation. In particular, attitudes towards the integration of ICT (Information and Communication Technology) in teaching refer to the ideas, preconceptions, beliefs, and opinions held by students regarding the incorporation of ICT into the teaching and learning process. These attitudes are influenced by the students' prior experiences with technology (Binder & Nierdele, 2006).

The Technology Acceptance Model (TAM) is a theoretical framework originally introduced by Davis to explain how individuals accept information systems based on rational behaviour theory. According to TAM, the actual use of a system depends on an individual's behavioural intention. This behavioural intention, in turn, is influenced by two key factors: behavioural attitude and perceived usefulness. Notably, both perceived usefulness and ease of use have a substantial impact on one's behavioural attitude. Additionally, perceived ease of use, in combination with external variables, plays a crucial role in shaping perceived usefulness. As a result, both perceived usefulness and ease of use are critical determinants of a user's behavioural intention, and they both have a positive influence (Shao, 2020; Woodeson, 2022). According to Limna, Kraiwanit, and Jangjarat (2023), the concept of "easy to use" relates to how users perceive a system's ease of understanding and the time required for effective utilisation. Perceived ease of use reflects a user's willingness to engage with a system that demands minimal effort on their part. This aspect holds significant importance not only during the initial adoption of technology but also for its sustained usage. Researchers argue that when a technology is perceived as easy to use, it increases the likelihood of users actively using the platform (Fearnley & Amora, 2020; Prastiawan, Aisjah, & Rofiaty, 2021). On the other hand, perceived usefulness pertains to the extent to which a user believes that technology can enhance their effectiveness and performance. It represents an evaluation of the benefits offered by technology in simplifying the attainment of desired services. An individual's inclination to use technology is often based on a positive assessment of its perceived usefulness. When an individual views technology as beneficial, they are more inclined to make use of it. The advantages associated with technology use are closely linked to factors such as productivity, effectiveness, and so on (Wardana et al., 2022).

Facilitating conditions in education technology encompass the essential elements and support systems required for the effective integration of technology into educational settings. This includes having the necessary infrastructure, technical support, and training for educators and students. In addition, it involves aligning technology with the curriculum, providing access to digital content, and ensuring data management systems are in place. Clear policies, collaboration, budgeting, accessibility, and inclusivity considerations are also key aspects of facilitating conditions in education technology. These conditions are essential for creating an environment where technology enhances the learning experience and supports educational goals (Khechine, Raymond, & Augier, 2020; Limna et al., 2022; Qiao et al., 2021).

Security and privacy in educational technology are paramount concerns that revolve around safeguarding data, protecting user information, and ensuring the overall safety of technology-enabled learning environments (ABP News Bureau, 2023). Acknowledging the substantial expenses associated with cyber risks, research has progressively shifted its attention towards examining the precautions and behaviours exhibited by internet users to safeguard their devices. It has been observed that the capacity to make choices, rather than being dictated or presented with a single option, yields positive outcomes. Individuals tend to be more internally motivated, demonstrate enhanced performance in tasks they have personally chosen, and experience greater satisfaction with their decisions while also feeling a heightened sense of control (Limna, Kraiwanit, & Siripipattanakul, 2023).

Lin et al. (2020) explored how Science, Technology, Engineering, and Mathematics (STEM) education impacts middle school students' attitudes toward technology and their abilities in technological inquiry. They utilised the 6E Learning by DeSIGN™ model, as proposed by the International Technology and Engineering Educators Association in the United States, to create a STEM practical activity with a 6E-oriented approach. The findings indicated that implementing the 6E teaching strategy had a positive impact on middle school students' attitudes toward technology and their technological inquiry abilities. However, it's worth noting that these effects were not statistically different from those observed in the control group that received a problem-solving teaching strategy. Furthermore, Liu and Ma (2023) extended these findings by conducting structural equation modelling analyses, uncovering profound insights. Their research indicated that while perceived ease of use may not directly predict learners' attitudes, it exerts its influence indirectly through the intermediary variable of perceived usefulness. Additionally, the study illuminated that learners who hold positive attitudes toward the utility of ChatGPT are more inclined to exhibit a heightened behavioural intention. This elevated behavioural intention, in a noteworthy cascading effect, strongly and positively correlates with their tangible and real usage of ChatGPT for English learning, extending its impact well beyond the confines of the classroom.

Rafique et al. (2020) examined the acceptance of mobile library applications using an extended TAM and found that perceived usefulness and perceived ease of use significantly predict users' intentions to use these applications. Alismaiel, Cifuentes-Faura, and Al-Rahmi (2022) investigated how university students' behaviour and intentions to use social media for academic purposes were influenced during the COVID-19 pandemic. They discovered that 1) using social media for collaborative learning and student engagement directly enhances the perception of usefulness, ease of use, and enjoyment; 2) perceived usefulness, ease of use, and the level of enjoyment positively impact students' attitudes toward using social media for academic purposes; 3) the relationship between key TAM attributes and the intention to use social media is mediated by one's attitude toward its use; and 4) students' attitudes and intentions regarding social media directly and positively affect their academic performance, particularly during the challenging circumstances of the COVID-19 pandemic.

In research conducted by Limna et al. (2023), several concerns emerged regarding the adoption of ChatGPT in educational settings. Participants expressed apprehensions about the accuracy of information provided by the chatbot and the possible diminishment of personal interaction with teachers. Furthermore, there was a notable emphasis on the importance of privacy and data security as significant concerns when considering the use of ChatGPT in education. Huallpa (2023) also indicated that participants stressed the necessity for explicit institutional standards regarding privacy and data security.

In this study, the researchers explore various factors influencing the adoption of ChatGPT as a study tool among students. Perceived usefulness refers to the belief that ChatGPT can enhance academic performance and simplify tasks, establishing its merit as an educational aid. Conversely, perceived ease of use reflects the idea that ChatGPT is user-friendly and easy to engage with, thus increasing its likelihood of adoption. Attitude plays a pivotal role in shaping students' willingness to embrace ChatGPT as an educational tool. Positive attitudes arise from the belief that ChatGPT can improve academic performance, streamline tasks, and positively contribute to the learning experience. Conversely, negative attitudes may result from concerns regarding ChatGPT's reliability, credibility, or ethical implications. Investigating these attitudes provides valuable insights into students' acceptance or resistance to adopting ChatGPT. Privacy and security are paramount when students utilise AI tools like ChatGPT. It is essential to assess students' comfort with sharing academic data with ChatGPT and to evaluate the safeguards in place for data protection. A robust privacy framework can alleviate concerns and instil trust in ChatGPT's security. Security encompasses not only data privacy but also safeguarding the system against potential threats like hacking and manipulation. Evaluating measures such as encryption, access controls, and system integrity is crucial to instil confidence in ChatGPT's reliability. Furthermore, the study delves into facilitating conditions, which encompass the resources and knowledge available to individuals for utilising ChatGPT. When individuals have access to more facilitating conditions, such as abundant resources and knowledge, they are more likely to extensively use ChatGPT. Lastly, the intention to use ChatGPT signifies students' motivation and expressed willingness to incorporate it into their academic activities. This intention underscores their readiness to embrace ChatGPT as a valuable resource in their studies. Figure 1 illustrates the study's conceptual framework, with hypotheses presented as follows:

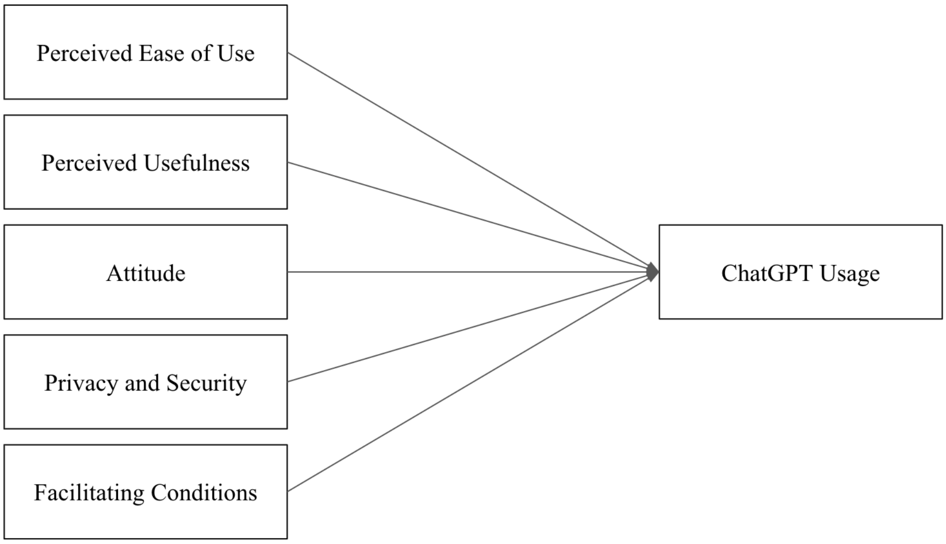

Figure 1. Conceptual Framework

H1: Perceived ease of use significantly influences ChatGPT usage.
H2: Perceived usefulness significantly influences ChatGPT usage.
H3: Attitude significantly influences ChatGPT usage.
H4: Privacy and security significantly influence ChatGPT usage.
H5: Facilitating conditions significantly influence ChatGPT usage.

RESEARCH METHODOLOGY

This study employed a quantitative research approach. The data collection for this quantitative study involved the use of online closed-ended questionnaires employing Likert's Rating Scale. A five-point Likert Scale was employed to evaluate the main variables in this study from 5 (strongly agree) to 1 (strongly disagree). The questionnaire items were meticulously crafted using reliable and validated research data. The validity of the measurement instruments was assessed, which refers to the accuracy with which a measurement quantifies the researcher's intended concept (Siripipatthanakul et al., 2023). Furthermore, the questionnaire was pre-tested on 30 respondents to obtain a dedicated questionnaire, as recommended by Doungpitak et al. (2023) and Thetlek et al. (2023). The data was gathered through an online survey created using Google Forms. This survey was disseminated through various online platforms, including Facebook, Line, and X (Twitter), following the recommendations of Duangsin et al. (2023). Adhering to the recommendations of Siripipatthanakul et al. (2022), the researchers provided an explanation of the study's purpose to the respondents and sought their willingness to participate before distributing the online questionnaires. The study's target population was an unknown number of Thai higher education students in Bangkok, Thailand. Samples were Thai higher education students in Bangkok, Thailand whose age was over 18 years old. According to Napawut et al. (2022) and Singharat et al. (2023), a standard survey usually has a confidence level of 95%. A minimum of 385 samples at p=0.5 using probability sampling (Stratified Random Sampling) with a sample error of 5% and a precision level of 95% are required to collect data. The study's sample size was 400 respondents. Convenience sampling was employed.

Data analysis was performed using analytical software, employing statistical methods for examination. Descriptive statistics were utilised to outline general characteristics, including gender, age, educational level, behaviours and factors associated with ChatGPT usage. This information was presented in the form of frequency tables, percentages, and means. Inferential statistics were used to test hypotheses and ascertain relationships between independent and dependent variables, following various assumptions.

RESULT

In this study, a total of 400 higher education students in Bangkok, Thailand, participated by completing online questionnaires. The collected data from these respondents were then coded and subjected to thorough analysis for research purposes.

Table 1. Descriptive Statistics

Hypotheses	N	Mean	Std. Deviation
H1	400	3.947	0.693
H2	400	4.047	0.673
H3	400	4.013	0.637
H4	400	3.672	0.796
H5	400	3.899	0.722

Table 1 presents descriptive statistics for each of the hypotheses (H1, H2, H3, H4, H5) in the study. In this study, there were 400 participants for each hypothesis. For H1, the average score was 3.947. For H2, the average score was 4.047. For H3, the average score was 4.013. For H4, the average score was 3.672. For H5, the average score was 3.899. Furthermore, the standard deviation quantifies the extent of variation or dispersion in the data. A higher standard deviation implies greater variability among the responses. For H1, the standard deviation was 0.693, for H2 it was 0.673, and for H3, it was 0.637, indicating relatively lower variability in comparison to H4. H4 exhibited a standard deviation of 0.796, signifying a higher level of variation in the data compared to the other hypotheses. Lastly, H5 had a standard deviation of 0.722, indicating the level of variability within this hypothesis.

Table 2. Reliability Statistic

Cronbach's Alpha	N of Hypotheses
0.889	5

Table 2 provides information about Cronbach's Alpha, a measure of internal consistency reliability used to assess the reliability of a set of questions in a research instrument, such as a questionnaire or survey. In this case, the value of Cronbach's Alpha is 0.889, and it pertains to a total of 5 hypotheses. Cronbach's Alpha assesses the degree to which a set of items (in this case, the hypotheses) in a research instrument consistently measure the same underlying construct or concept. The value of 0.889 indicates a high level of internal consistency among the hypotheses. Thus, the items within these hypotheses are highly correlated with each other, suggesting that they are measuring the same underlying concepts effectively.

Table 3. Model Summary

Model	R	R^2	Adjusted R^2	Std. Error of the Estimate
1	0.624[a]	0.389	0.381	0.692

a. Predictors: (Constant), H1, H2, H3, H4, H5

As indicated in Table 3, these statistics offer valuable insights into the performance of the regression model. An R value of 0.624 implies a moderate positive linear relationship between the variables. The coefficient of determination (R^2) for predicting ChatGPT usage is 0.389, indicating that approximately 38.9% of the variability in ChatGPT usage can be explained by the predictors included in the model. This means that the independent variables in the model collectively account for about 38.9% of the variation observed in ChatGPT usage, highlighting their significance in explaining the phenomenon being studied.

Table 4. Coefficients[a]

Model		Unstandardised B	Coefficients Std. Error	Standardised Coefficients Beta	t	Sig.	Results
1	(Constant)	0.633	0.241		2.629	0.009	
	H1	-0.030	0.074	-0.024	-0.411	0.681	Rejected
	H2	0.106	0.082	0.081	1.301	0.194	Rejected
	H3	0.430	0.092	0.312	4.663	0.000	Accepted
	H4	-0.021	0.059	-0.019	-0.354	0.732	Rejected
	H5	0.388	0.084	0.319	4.635	0.000	Accepted

a. Dependent Variable: ChatGPT Usage

The statistical analysis conducted in this study, as shown in Table 4, offers a comprehensive understanding of the determinants influencing ChatGPT usage among higher education students in Bangkok, Thailand. Among the hypotheses tested, two were found to be statistically significant. Specifically, the hypothesis concerning students' attitudes (H3) was accepted with a significance level of 0.000, demonstrating that students' positive or negative attitudes significantly influence their ChatGPT usage behaviour. Furthermore, the hypothesis related to facilitating conditions (H5) was also accepted with a significance level of 0.000, indicating that the availability of resources and knowledge plays a pivotal role in encouraging extensive ChatGPT usage among students. Conversely, three hypotheses were rejected. Perceived ease of use (H1) and perceived usefulness (H2) did not exhibit statistically significant relationships with ChatGPT usage, as indicated by significance levels of 0.681 and 0.194, respectively. Similarly, privacy and security considerations (H4) were not found to significantly influence ChatGPT usage, with a significance level of 0.732. These findings emphasise the importance of considering students' attitudes and the presence of facilitating conditions when promoting the adoption of ChatGPT in educational contexts, while also acknowledging the limited impact of perceived ease of use, perceived usefulness, and privacy and security concerns in this specific study.

DISCUSSION

This study introduces a series of hypotheses aimed at understanding the key factors that influence the adoption of ChatGPT in educational contexts in Thailand. The results indicated that attitudes were found to have a statistically significant influence on ChatGPT usage, highlighting the pivotal role of students' perceptions and beliefs in shaping their adoption of this educational tool. Additionally, facilitating conditions, encompassing resources and knowledge, were also identified as significant determinants, underlining the importance of a supportive environment for technology adoption. The findings of this study align with several previous research. For instance, Sabti and Chaichan (2014) identified gender-based differences in attitudes toward the use of computer technologies in English learning. Their research revealed that female students displayed more favourable attitudes and greater enthusiasm for employing computer technologies in English learning compared to their male counterparts. Moreover, Sitthipon et al. (2022) discovered that facilitating conditions had the highest predictive power on the intention to use healthcare chatbots and apps.

On the other hand, the hypotheses related to perceived ease of use, perceived usefulness, and privacy and security considerations did not yield statistically significant results. This suggests that students' perceptions of the ease of using ChatGPT, its usefulness, and their concerns about privacy and security did not have a strong direct impact on their actual usage. However, in a study by Bonsu and Baffour-Koduah (2023), a statistically significant relationship was established among Ghanaian university students' perceptions, specifically their perceived usefulness and ease of use, of ChatGPT, and their intentions to incorporate this technology into higher education settings. Sallam et al. (2023) emphasised the importance of considering various factors, including risk perceptions, perceived usefulness, ease of use, attitudes toward technology, and behavioural considerations, when integrating ChatGPT into healthcare education. Huallpa (2023) found that participants generally perceived the integration of Chat GPT as moderately accessible and held moderately positive social attitudes toward it. They demonstrated an understanding of Chat GPT's significance and its role in providing personalised educational opportunities. Additionally, participants underscored the importance of establishing clear institutional standards regarding privacy and data security.

CONCLUSION

This study sheds light on the key factors influencing the adoption of ChatGPT as an educational tool among higher education students in Bangkok, Thailand. The findings emphasise the substantial role of attitudes in driving ChatGPT usage, affirming that students' beliefs and perceptions significantly shape their decision to embrace this technology for their academic endeavours. Furthermore, the study underscores the critical importance of facilitating conditions, such as access to resources and knowledge, in fostering a conducive environment for the successful integration of ChatGPT into the educational landscape.

Nevertheless, it is vital to highlight that perceived ease of use, perceived usefulness, and considerations regarding privacy and security did not demonstrate statistical significance in their role as determinants of ChatGPT usage within the scope of this study. This implies that, while these elements hold significance in the broader context of technology adoption, they did not directly impact students' practical utilisation of ChatGPT in the specific educational environment under investigation. These findings underscore the intricate nature of technology adoption and stress the necessity for a comprehensive understanding of the multifaceted factors at play when students interact with AI-driven educational tools like ChatGPT.

The study's findings have several executive, policy, and academic implications. For executives and educational leaders, understanding the significant factors that influence ChatGPT usage among higher education students in Bangkok, Thailand, is crucial for making informed decisions about technology integration in educational institutions. These decision-makers should consider factors like facilitating conditions and attitude when implementing and promoting the adoption of ChatGPT. From a policy perspective, education authorities and institutions may need to establish guidelines and standards that address privacy and security concerns related to the use of educational technology like ChatGPT. Policies should also promote the creation of favourable facilitating conditions and encourage a positive attitude toward technology adoption in education. In the academic realm, this study underscores the importance of considering the multifaceted nature of technology adoption when conducting research and designing educational programs. Academic institutions can benefit from integrating user experience, practicality, and security considerations into their curriculum and technology implementation strategies to enhance the acceptance and effectiveness of tools like ChatGPT in diverse learning environments.

This study has limitations and offers valuable recommendations for future research. The limitations include the use of convenience sampling, which may introduce bias and limit generalizability, as well as the reliance on self-reported data, which could be affected by response and social desirability bias. Additionally, the cross-sectional design provides a snapshot of ChatGPT usage without capturing changes over time. The recommendations for future studies involve diversifying sampling methods to improve representativeness, considering mixed-methods approaches to gain a deeper understanding, conducting longitudinal research to track changes, and comparing ChatGPT with other educational technologies. Intervention studies are suggested to enhance factors influencing ChatGPT acceptance, and a focus on privacy and security concerns is encouraged for safer usage. Implementing these recommendations in future research can advance our comprehension of technology adoption in educational contexts and lead to the development of more effective and secure educational tools like ChatGPT.

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Factors Affecting the Brand Image of International Schools Through Parents' Perceptions in Bangkok, Thailand

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ABSTRACT

Objective: The perception of international school brands among parents plays a pivotal role in enrollment, reputation, competitiveness, and long-term viability. A positive brand image builds trust, draws in students, and solidifies a school's standing as a respected educational institution, delivering benefits to the school and the surrounding community. This research investigates the factors influencing the perception of international school brands among parents in Bangkok, Thailand. In the context of the research on international schools in Bangkok, Thailand, it is essential to consider the marketing mix, often referred to as the 7Ps, as these elements significantly impact how parents perceive these institutions.

Methodology: A quantitative approach was utilised, collecting data from parents of students enrolled in international schools in Bangkok, Thailand. The data was collected from 392 respondents through the use of online questionnaires. Convenience sampling was employed. Statistical methods adopt descriptive and multiple regression models for data analysis.

Results: Regarding examining the marketing mix (7Ps) for international schools, it was found that factors like premium services, programmes, and prominence significantly influenced brand image, but not promotion, persuasion, or personnel. Overall, these factors played a role in shaping the brand image of international schools in Bangkok. Additionally, brand awareness emerged as a significant brand image driver for international schools in Bangkok, Thailand.

Implications: These findings have implications for school executives and other stakeholders in international schools in Bangkok, Thailand, suggesting that they should focus on factors of 7Ps like premium services, programme offerings, and prominence in the educational landscape to enhance their brand image among parents. In addition, the schools could improve brand image by enhancing brand awareness among parents.

Keywords: *Brand Awareness, Brand Image, International School, 7Ps, Marketing Mix*

INTRODUCTION

Studying is considered essential for one's future life. The ability of individuals to prepare themselves with knowledge and skills for their future work and lives is crucial. This preparation begins with basic education and extends to advanced studies, including leading domestic and international universities. Education is crucial in achieving success in life, and it is a significant variable that can lead to greater acceptance and recognition in the workplace for those who have completed their studies (Campbell, 2006; Greenhill, 2010; Limna et al., 2021). Thus, preparing for higher education should start at the foundational level. In Thailand, there are both government-run and private schools. The Basic Education Commission manages government schools, whereas individual groups or licenced associations oversee private schools (Termes et al., 2020; Wei & Mhunpiew, 2020). International schools these days have become increasingly popular due to their focus on global education and proficiency in languages like English. These schools typically offer English-based curricula and encourage multilingualism from an early age. These institutions provide specialised and adaptable curricula, allowing students to prepare for future careers while pursuing other interests. Parents should prioritise academic excellence, qualified teachers, and diverse extracurricular opportunities when choosing an international school. These factors contribute to a well-rounded education that prepares students to positively impact the world (Kim & Mobrand, 2019; Namraksa & Kraiwanit, 2023).

Parents are considered customers in the education industry, and their past experiences often influence their behaviour. Positive experiences lead to satisfaction and a likelihood of returning, while negative ones result in avoidance. As a result, previous interactions influence customer expectations. In education, "parental expectations" are parents' realistic beliefs regarding their child's future academic achievements, such as course grades, educational attainment, or college attendance. These expectations are based on their evaluation of their child's academic abilities and available resources. Researchers usually measure parental expectations by asking parents how far they believe their child will progress in school or what grades they anticipate their child will achieve. Occasionally, student perceptions of parental expectations are used as a proxy for the parents' expectations (Breidenstein et al., 2020; Namraksa & Kraiwanit, 2023).

The 7Ps marketing mix is a comprehensive framework used by businesses, particularly in service industries, to plan and manage their marketing strategies effectively. The 7Ps marketing mix is especially useful for businesses in service industries like hospitality, healthcare, banking, consulting, as well as education, where the intangible nature of the service and customer interactions play a significant role in the overall customer experience. It provides a more comprehensive framework for planning and managing marketing activities in these sectors (Awara & Anyadighibe, 2014; Siripipatthanakul & Chana, 2021).

The perception of international school brands among parents is important as it significantly impacts various aspects of the schools' functioning. It serves as a linchpin in enrollment rates, overall reputation, competitive positioning, and the long-term sustainability of these institutions. A positive brand image fosters trust among parents, attracts students, and cements the school's position as a revered and trusted educational establishment. These positive outcomes extend beyond the school's walls, benefiting the institution and the wider community it serves. To shed light on these critical factors, this research investigates the underlying determinants that shape parents' perceptions of international school brands in Bangkok, Thailand.

LITERATURE REVIEW

According to Bangphon (2023), ISC Research (2023) and Supachart (2023), the 21st century has witnessed a significant surge in the number of international schools across various regions, particularly within the bustling Bangkok metropolitan area of Thailand. This proliferation can be attributed to a confluence of factors, including the escalating demands of the economy, evolving societal needs, and the burgeoning residential requirements of a diverse global population. As a consequence, the international school sector has become a hotbed of competition, with a particularly pronounced impact on smaller-sized institutions that may be constrained by financial resources. The increasing number of international schools has transformed the educational landscape, turning it into a highly competitive marketplace. Smaller-sized international schools, in particular, are grappling with the challenges posed by this intensified competition. In this dynamic environment, staying relevant and thriving demands a concerted effort on the part of these schools to differentiate themselves and carve out a distinctive identity within the educational ecosystem. To thrive and secure their foothold in the ever-expanding international education market, international schools, especially those with limited financial resources, must prioritise the development of a strong brand image. Achieving brand recognition and fostering a positive reputation is paramount. This process involves not only offering high-quality education but also actively engaging in strategic marketing activities. By doing so, these schools can effectively communicate their unique value propositions and attract students and parents in an increasingly discerning and competitive landscape.

7Ps of the Marketing Mix

Higher education institutions require a well-structured, comprehensive marketing strategy that effectively communicates across the institution. The services marketing mix, often referred to as the 7Ps, serves as a valuable tool for these institutions, enabling them to tailor their service offerings to meet the specific needs of their customers, which are the students. In education marketing, the 7Ps of the marketing mix stand out as the most critical factors for achieving success. Recognising that marketing can significantly influence consumer behaviour and that the services marketing mix can assist higher education institutions in crafting a comprehensive and carefully considered service offering, it's essential to understand the seven elements of the services marketing mix: service product, price, place, promotion, people, process, and physical evidence (Chawla, 2013). In this study, the 7Ps marketing mix factors comprise: premium services, prominence, promotion, price, programme, persuasion and personnel. These elements play a pivotal role in shaping how a school is perceived by parents and students. Premium services emphasise the provision of exceptional and unique offerings to set the institution apart. Prominence focuses on establishing a strong reputation and visibility within the educational landscape. Promotion involves the strategic communication and marketing efforts that showcase the school's strengths. Price considerations balance affordability with perceived value for money. The curriculum and educational offerings fall under the purview of the programme factor. Persuasion centres on effectively communicating the school's distinct advantages and value proposition. Lastly, personnel encompasses the qualifications, dedication, and reputation of the teaching and administrative staff, contributing significantly to the overall quality of the educational experience. These seven factors collectively define a school's market presence and competitiveness in the dynamic international education sector (Ivy, 2001; Ivy 2008).

Ivy (2008) introduced a novel marketing mix model that relied on the attitudes and viewpoints of Master of Business Administration (MBA) students regarding the marketing strategies employed by business schools in South Africa. The market for postgraduate business education has become increasingly competitive, particularly in attracting students to pursue their flagship degree, the MBA. The conventional marketing tools, historically grouped into categories such as the 4Ps (product, price, place, and promotion), 5Ps (adding people), and 7Ps (adding physical facilities and processes), may not fully address the complexities of this market. The findings revealed seven distinct underlying factors within the marketing activities of these business schools. Some of these factors encompassed similar aspects as the traditional marketing mix, including people, promotion, and price. However, four elements emerged: programmes, prominence, prospectus, and premiums. Additionally, Ndofirepi et al. (2020) focused on the challenges and opportunities in the African higher education market, characterised by diverse universities. Despite the shared interest in exploring this market, there was a notable shortage of research in this area. The study aimed to fill this gap by providing an overview of the African higher education market from a marketing perspective, using the 7Ps of a marketing framework. Critical challenges within the market were highlighted, including limited access to higher education, the role of facilities in shaping students' perceptions, and the complexities faced by international branch campuses operating as learning hubs in Nigeria. The study recommended university managers and policymakers address the strategic marketing implications. While there were opportunities for universities and international partners to tap into emerging markets in Africa, a deep understanding of how the 7Ps influenced marketing strategies was critical.

Brand Perceptions

At the educational institution level, brand perception holds significant importance. This is because brand perception influences decision-making and impacts brand image (Mulyono, 2016). If consumers recognise an educational institution, it can lead to brand awareness, a positive image, and better decision-making compared to an institution that consumers are unfamiliar with (Brewer & Zhao, 2010). One fundamental component of brand value, brand equity, is significantly derived from brand perception. This is considered a fundamental key that guides consumer decision-making. Brand perception includes two crucial aspects: brand recognition, where consumers can identify the brand, and brand recall, where consumers can recall the brand. Both components are essential for consumer decision-making and contribute to increasing brand knowledge (Moisescu, 2009; Keller & Brexendorf, 2018; TMDesign, 2023). In higher education marketing, effective strategies have undergone significant transformations in recent years. The emergence of social media and the proliferation of higher education options have introduced a competitive dimension to student advertising that demands attention. Brand awareness, which refers to how the public perceives a higher education institution, directly impacts application and enrollment figures. It is crucial for institutions to ensure that their brand is not only well-established but also widely recognised. Institutions must proactively cultivate brand awareness to reach potential students, establish a broad reputation, and attract more recruits (The Glacier Team, 2019). The concept of university image is the collective beliefs held by individuals about a university. The university's brand image in education marketing has been recognised as a significant competitive asset. A university's brand image is enhanced as its reputation grows stronger. Consequently, university chancellors have become increasingly aware of the importance of cultivating a strong brand presence. Thus, they have allocated more excellent resources towards enhancing the image of the universities under their management (Nasib et al., 2022; Siripipattanakul et al., 2022).

Given the global competitiveness of higher education, the image of the country and the university plays a pivotal role in attracting more international students to Malaysia. Mun et al. (2018) conducted a study aimed at investigating the factors that impact international students' decisions when choosing both their destination country and university for tertiary education. The perception of a destination was intricately connected to its affective image, which subsequently influenced students' intentions to recommend that particular destination to others. A university's individual reputation and image play a vital role in shaping students' perceptions and ultimate decisions regarding enrollment. Mulyono (2016) conducted a study investigating several relationships in the context of brand perception. Specifically, the study examined the impact of brand awareness on brand image, the influence of brand image on perceived value, the connection between perceived value and satisfaction, the relationship between brand image and satisfaction, and the effect of satisfaction on loyalty. The study's findings revealed a positive and significant correlation between brand awareness and brand image. This implies that when students have a higher level of brand awareness regarding an institution, it positively influences their perception of the institution's brand image, ultimately enhancing it.

RESEARCH METHODOLOGY

This research adopted a quantitative research approach. Data collection for this quantitative study was conducted using online closed-ended questionnaires that utilised the Likert's Rating Scale. The Likert scale employed a five-point rating system, ranging from 5 (strongly agree) to 1 (strongly disagree), to assess the main variables in this study. The questionnaire items were carefully constructed using reliable and validated research data. The measurement instruments' validity was evaluated, which indicates the extent to which a measurement accurately captures the researcher's intended concept (Shaengchart et al., 2023). Additionally, the questionnaire underwent a pre-test involving 30 respondents to refine it, following the recommendations of Jangjarat et al. (2023). Data collection was conducted through an online survey created using Google Forms. In accordance with the guidance of Napawut et al. (2022), the researchers explained the study's purpose to the respondents and obtained their consent before disseminating the online questionnaires. The population involved in this research consisted of parents of students currently attending international schools. These parents have already decided to enrol their children in international schools and have recommended them through social media. The exact number of parents was unknown. According to Chana et al. (2021), Limna et al. (2022) and Siripipatthanakul et al. (2023), a standard survey usually has a confidence level of 95%. A minimum of 385 samples at $p = 0.5$ using probability sampling (Stratified Random Sampling) with a sample error of 5% and a precision level of 95% are required to collect data. The study's sample size was 392 respondents. Convenience sampling was employed.

Descriptive statistics were indeed employed to offer a comprehensive portrayal of the sample group's characteristics. This entailed calculating frequencies, means, and standard deviations to gain insights into the central tendencies and variances within the dataset. Moreover, in addition to descriptive statistics, inferential statistics were harnessed to rigorously evaluate the research hypotheses and extract meaningful insights from the data. Specifically, multiple regression analysis was utilised to scrutinise the relationships between independent and dependent variables. These inferential statistical methods enabled the researchers to draw informed, statistically significant inferences about the research questions and hypotheses, strengthening the overall robustness of the study's findings.

RESULTS

The sample group was predominantly female (64.5%), with a significant portion falling in the age range of 41 to 50 years (45.4%). Approximately half of the participants held master's degrees (49.8%), and a substantial proportion reported average incomes between 50,001 and 100,000 Baht (46.7%). Concerning annual tuition fees, a noteworthy number indicated fees ranging from 250,001 to 500,000 Baht per academic year. Most parents had children enrolled in schools offering the British Curriculum (52%), at the middle school level (44.4%). Additionally, most preferred schools focus on the Chinese language for their children's education (55.4%). Most parents have not yet planned to send their children to study abroad (69.4%).

Predicting Model of the Marketing Mix (7Ps) on International Schools' Brand Image

Table 1. The Influence of Marketing Mix (7Ps) Among Parents of Students on the Brand Image of International Schools in Bangkok, Thailand (n = 392)

7Ps	β	Beta	Sig.
Constant	2.421		0.001***
Premium Services (X_1)	0.353	0.254	0.001***
Prominence (X_2)	0.178	0.096	0.024*
Promotion (X_3)	0.036	0.076	0.520
Price (X_4)	- 0.061	- 0.096	0.293
Programmes (X_5)	0.268	0.271	0.001***
Persuasion (X_6)	0.006	0.008	0.771
Personnel (X_7)	0.003	- 0.031	0.961

Dependent Variable ($\hat{Y}$): Brand Image
Predictors (X): Premium Services (X_1), Prominence (X_2), Promotion (X_3), Price (X_4), Programmes (X_5), Persuasion (X_6) and Personnel (X_7)
R = 0.530; R^2 Adjusted = 0.281; R^2 = 0.266; Standard Error of Estimate = 0.550
*p < 0.05; **p < 0.01; ***p < 0.001

From Table 1, the results of the multiple regression analysis show that the coefficient of determination (R^2) is 0.266. This indicates that the 7Ps components of the international school business, including premium, prominence, promotion, price, programme, prospectus, and people factors, can explain 26.6% of the variation in the brand image of international schools in Bangkok, Thailand. Specifically, the premium factor (β = 0.353, t = 4.635, p-value = 0.001) and the programme factor (β = 0.268, t = 4.788, p-value = 0.001) have a statistically significant influence on the brand image of international schools in Bangkok at a significance level of 0.001. Additionally, the prominence factor (β = 0.178, t = 2.262, p-value = 0.024) has a statistically significant influence on the brand image of international schools in Bangkok at a significance level of 0.05. On the other hand, the promotion, price, prospectus, and people factors were found not to have statistically significant effects. The coefficients of these factors can be used to form a multiple regression equation for predicting the brand image of international schools in Bangkok. The equation is shown as follows:

$$\hat{Y} = 2.421 + 0.353X_1{}^{***} + 0.178X_2{}^{*} + 0.036X_3 - 0.061X_4 + 0.268X_5{}^{***} + 0.006X_6 + 0.003X_7$$

Predicting Model of Brand Awareness on the Brand Image of International Schools

Table 2. The Influence of Brand Awareness Among Parents of Students on the Brand Image of International Schools in Bangkok, Thailand (n = 392)

Brand Awareness	β	Beta	Sig.
Constant	4.715		0.001***
Brand Awareness (X_1)	0.219	0.250	0.001***

Dependent Variable ($\hat{Y}$): Brand Image
Predictor (X_1): Brand Awareness
R = 0.348; R^2 Adjusted = 0.121; R^2 = 0.105; Standard Error of Estimate = 0.608
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$

From Table 2, it is observed that the coefficient of determination (R^2) of 0.105 indicates that brand awareness can explain 10.5% of the variation in factors (7Ps) influencing the brand image of international schools in the Bangkok metropolitan area. The influence of parental brand awareness (β = 0.219, t = 0.250, p-value = 0.001) on the brand image of international schools in Bangkok is statistically significant at the 0.001 level. The equation is shown as follows:

$$\hat{Y} = 4.715 + 0.219X_1{}^{***}$$

DISCUSSIONS

This study investigated the factors influencing the perception of international school brands among parents in Bangkok, Thailand. The research identified that factors such as premium features, programme offerings, and prominence significantly influence the brand image of international schools in Bangkok, Thailand. The study also revealed that parental brand awareness statistically influences brand image at 0.001. The results of this study align with previous research. For instance, Asiah et al. (2022) revealed that the 7Ps marketing mix approach for educational institutions encompasses various elements, each playing a crucial role in shaping the institution's image and reputation. These components include product-related factors like the institution's history, vision, mission, curriculum, technological resources, and considerations related to pricing, place, promotion, people, processes, and the physical environment. Understanding and effectively managing these components is vital for educational institutions striving to thrive in a competitive landscape and meet the expectations of students, parents, and other stakeholders. Enache (2011) also presented the product, price, placement, promotion, people, process, and physical evidence strategies. The study highlighted the unique roles of each strategy within the educational market and emphasised the significance of synergy effects. The advantages of employing the 7Ps approach were underscored. Furthermore, Cakmak (2016) underscored the impact of brand perception and access to social media information on brand image. Educational institutions can leverage these channels to foster meaningful connections with parents or students. Bilgin (2018) stressed that brand perception encompasses values like names, symbols, and product brands, while brand image resides within consumers' thoughts and emotions, ultimately shaping their assessments of the brand. Additionally, Namraksa and Kraiwanit (2023) uncovered parental expectations regarding sending their children to international schools in Nonthaburi, Thailand. Regarding teaching and learning courses, parents anticipated that these courses would nurture creativity and assertiveness in students. Concerning the school's reputation in management, parents looked for a solid reputation backed by reliable teaching quality and effective, transparent management policies. As for the school's physical location, parents desired a secure building equipped with ample facilities. Finally, in adapting to the digital age, parents expected the inclusion of lessons on utilising electronic devices and various online media platforms.

CONCLUSIONS

This study has shed light on the crucial role parents' perceptions of international school brands in Bangkok, Thailand, play in affecting enrollment rates, reputation, competitiveness, and long-term sustainability. A positive brand image fosters trust and attracts students and solidifies a school's position as a respected educational institution, with far-reaching benefits for the school and the surrounding community. Through a quantitative approach involving 392 respondents who were parents of students enrolled in international schools in Bangkok, Thailand, this study identified key demographic factors influencing brand image. Additionally, it underscored the significance of factors like premium services, programme offerings, and prominence in the educational landscape; however, promotion, personnel, and percussion are still crucial according to the marketing mix model (7 Ps) in the overall explanation. Moreover, brand awareness is useful in shaping perceptions of brand image among parents. The explanation is a bit low; sometimes satisfaction and loyalty (behavioural intention) should be considered for the outcome of further study, brand image and awareness could be the mediators. These findings offer valuable insights for school leaders and stakeholders, suggesting strategies to enhance brand image and cater marketing efforts to specific parent segments. This research contributes to a deeper understanding of the dynamics between international school brands and parents in Bangkok, Thailand, shedding light on avenues for continued growth and success in the competitive educational landscape.

While the study has provided valuable insights, some limitations should be considered, including sampling bias and the research's cross-sectional nature. Future studies should adopt a more diverse and representative sample to advance the understanding, consider longitudinal research designs and include qualitative approaches. Moreover, exploring the impact of brand perception on various outcomes is critical. These insights will be invaluable for school administrators, executives, educators, and stakeholders as they seek to enhance their brand image and cater to parents' diverse needs and expectations in the ever-evolving education sector.

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Artificial Intelligence (AI) Adoption: The Case of the Malaysian Financial Industry

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ABSTRACT

Objective: Artificial Intelligence (AI) is regarded as a critical determinant of strategic planning and the creation of competitive advantage in modern business practices. This study aims to review the trend, opportunities and challenges of adopting AI in the Malaysian financial industry, as well as the potential impact of adopting AI in the financial sector.

Methodology: The qualitative research employed narrative synthesis and content analysis to systematically describe a phenomenon, adapting to organised information.

Results: AI application challenges have emerged in Malaysia's financial industry due to various disruptive opportunities in the Financial Technology (FinTech) arena. These challenges also bring forth threats and concerns for incumbent stakeholders in the industry. Given its indispensable role in managing and analysing vast, intricate datasets to uncover patterns and insights, AI is considered a critical factor in establishing a competitive edge in contemporary business practices and strategic planning.

Implications: The study's results offer valuable insights for policymakers and potential adopters, enabling them to devise effective strategies. The vital insights for policymakers and industry stakeholders are to address AI's challenges and confirm the importance and potential challenges of implementing AI technology in the financial industry in Malaysia.

Keywords: *Artificial Intelligence (AI), Financial Industry, Digital Technology, Trends, Opportunities, Challenges, FinTech, Financial Services*

INTRODUCTION

"(Military) intelligence is the key to war; without it, you cannot win" – Sun Tzu Art of War.

Since ancient days, information has been a vital element in political and economic affairs for effective and timely decision-making that decides the outcome of wars to firms forging a competitive advantage against their business rivals. As the world enters the 21st century, also referred to as "the "Information Age", competition among firms has reached an unprecedented era, credited to technological advancement. To cope with the intense competition, AI has gained substantial focus, both commercial and academic studies, due to its ability to perform complex tasks at an unprecedented efficiency level, potentially creating a competitive advantage against rivals. In the past two decades, substantial resources have been invested in AI. This phenomenon is motivated by the consensus of the industries that AI is emerging as an essential element of the new business landscape. It is driven by the general belief AI's ability to process the ever-expanding information needs of the Big Data era is a result of accelerated digitalization of all aspects of life since the late 20th century driven by the emergence of the internet. This rich information will enable firms to plan and implement necessary strategies to ensure their survival in the face of competition and value creation. Because of the 4.0 revolution in the financial sector, big data and AI have created a new industry called the "Fintech industry", which is rapidly emerging globally. Fintech is becoming a significant disruptor of the existing banking and finance industry due to providing the same but more innovative financial services as those provided in the traditional banking and finance industry, except with lower fee costs and high margins. As AI is critical in managing and analysing extensive, complex data to discover patterns and insights, AI is regarded as a vital determinant of strategic planning and creating a competitive advantage in modern business practices.

This study reviews the trends, opportunities and challenges of adopting AI in the Malaysian finance industry. The findings from this study will provide meaningful insight to prospective adopters and policymakers to plan their strategies to capitalise on the benefits and mitigate the setbacks (Ali et al., 2019; Aly, 2022). The COVID-19 pandemic has increased the appetite for AI adoption in the financial sector, with key growth areas including customer relationship and risk management. For instance, banks are exploring leveraging their AI experience to handle the high volume of loan applications during the pandemic to improve their underwriting process and fraud detection. Three main advantages of AI are: 1) Reducing Error (Accuracy), 2 Multitasking (Efficiency), and 3) Working for more extended hours (Productivity). AI also has proven to be productive uses that affect the everyday life of the average consumer with face and voice recognition systems, interacting machines with human voices, data collection and organisation of market information, natural language processing, financial advisory, fraud and risk assessment, credit management, price setting, applications leading to Fintech, and integration with other emerging technologies including cryptocurrencies and blockchain (Milana & Ashta, 2021; Boukherouaa et al., 2021). Thus, the review article gives insight based on secondary data collection and content analysis regarding big data and artificial intelligence (AI), AI in the finance industry, AI in the Malaysian Finance Industry, Malaysian financial services legal framework, challenges and concerns, conclusions, and recommendations.

Research Objective

Artificial Intelligence (AI) is regarded as a critical determinant of strategic planning and the creation of competitive advantage in modern business practices. This study aims to review the challenges of adopting (AI) in the Malaysian financial industry that are important in investigating the potential impact of adopting AI in the financial sector.

Practical Implications

While AI provides various disruptive opportunities in the Financial Technology (FinTech) arena regarding data collection, analysis, safeguarding and streamlining processes, it also poses threats and concerns to incumbent stakeholders in the industry. This study provides vital insights for policymakers and industry stakeholders to address AI's challenges.

LITERATURE REVIEW

The articles have been selected from scholarly papers on the databases of Scopus, Google Scholar, Web of Science, etc., in a total of 33 papers from 2019 (5 papers), 2020 (9 papers), 2021 (6 papers), 2022 (7 papers), and 2023 (6 papers) adopting AI-based existing method based on the keywords of Artificial Intelligence (AI), Financial Industry, Digital Technology, Trends, Opportunities, Challenges, FinTech and Financial Services in the year of 2019-2023.

Big Data and Artificial Intelligence (AI)

Big Data and AI have experienced exponential growth in technologies and applications driven by the continuous improvement and breakthrough of platforms, algorithms and interaction methods. AI is often regarded as the next general-purpose technology with rapid, penetrating, and far-reaching use in many industrial sectors. While the term Big Data and AI has been used broadly and interchangeably in various academic studies and business contexts, it is essential to clarify its differences (Czarnitzki et al., 2023).

A consensual definition of Big Data is "*the Information asset characterised by such a High Volume, Velocity and Variety to require specific Technology and Analytical Methods for its transformation into Value.*" An essential feature of Big Data is that it is an information good, and information goods tend to be non-rival (i.e., not depleted by use) and produced under increasing returns to scale. Big Data is also associated with the massive computational resources needed to cope with the increasing volume and complexity of data from many sources, such as the internet and remote sensor networks, which embrace "cyber-physical systems, cloud computing, and the Internet of Things (IoT)", also known as Industry 4.0 (Mihet & Philippon, 2019).

There is no one universal definition of AI due to the difference in theoretical and practical values; AI is commonly defined as a machine (or process) that responds to environmental stimuli (or new data) and then modifies its operation to maximise a performance index, which its learning process is implemented using mathematics, statistics, logic, and computer programming that enables the AI model to be trained on data in an iterative procedure with parameter adjustment by trial and error using reinforcement rules. In a more general context, in a more general definition described AI as "a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation" (Wang, 2019; Kaplan & Haenlein, 2019). AI is the cornerstone of Industry 4.0 after automation, electrification and "informatization". AI adopts advanced machine learning, pattern recognition and data mining techniques to build AI models for information pre-processing, processing, refining and value-added services, which is widely used in the context of Industry 4.0, the Internet of Things and big data. AI strongly supports people's work and life and more effectively promotes the "informatization" and automation of an intelligent society (Lu, 2021). Hence, Big Data can be assumed to require massive data processing systems that often involve significant levels of process automation. Considering the features of Big Data and AI, Big Data is most apparent when viewed as a database for AI. As such, the focus on Big Data is commonly associated with AI.

Artificial Intelligence (AI) in the Finance Industry

In general, it is widely recognized that the financial industry has benefited from stimulus developments due to the application prospects of AI through a gradual adoption process. The application of AI in the financial sector is not only an analysis of financial data but is evidenced by the creation of various financial digital services. Within the framework of Big Data and AI, financial data is more diversified and robust, which are multiple models, structures and real-time changes that traditional systems cannot offer (Wang et al., 2020). AI-related literature on finance and financial markets studies generally can be categorised into six areas of interest, namely 1) Financial Management, 2) Financial Markets, 3) Banking, 4) Financial technology (Fintech), 5) Financial advisory services and price setting and 6) AI, Blockchain, and Bitcoin bonanza, which focuses on its functions as forecasting, decision-making, bankruptcy prediction, credit-scoring, and accounting and fraud issues as the critical application areas (Milana & Ashta, 2021).

AI applications often cover the entire value chain of the organisation, improve business processes, make them more efficient and less costly, and improve the reactivity of the organisation (Wamba-Taguimdje et al., 2020). Implementing AI-embedded big data analytics in Finance has many benefits, such as improving decision-making processes, enhancing accounting processes and compliance, boosting marketing campaigns, and providing better credit risk assessment procedures (Siew & Farouk, 2023) and fraud detection. Regarding AI adoptions, one cannot ignore the "elephant in the room" – the idea of machines replacing humans. On AI's impact on human resources and jobs, the World Economic Forum, 2018 predicted that AI technologies will significantly affect employment, especially in emerging economies, due to the greater scope for technological change within the manufacturing sector. In comparison, AI may potentially put many people out of jobs. AI technologies are also predicted to drive innovation and economic growth, leading to new employment (Dwivedi et al., 2021). As such, Big Data and AI undeniably impact jobs as they enable systems within organisations to expand rapidly, transforming business and manufacturing productivity and extending their reach into conventionally human-intensive aspects (Daugherty & Wilson, 2018; Miller, 2018). A positive relationship exists between the digital transformation index and economic development, labour productivity and job employment. AI directly affects job performance, and the bank's focus on AI improves productivity (Ramli & Wahab, 2023; Aly, 2022; Younnus, 2022).

Artificial Intelligence (AI) in the Malaysian Finance Industry

Many AI-related studies in Malaysia have been published in recent years. The impact of AI application can be a strategic and significant one; for instance, at the national level, studies suggest the efficacy of AI adoption in predicting GDP by comparing the neural network forecasting method and the government's estimation. It has been shown that the neural network method gives a smaller mean error value than traditional methods, which suggests the superior accuracy of forecasting GDP growth in Malaysia. The National Industrial Revolution 4.0 (4IR) Policy is estimated to increase the country's output by 30% across all sectors by the end of 2030, with AI playing a substantial role in attaining that target (Sanusi et al., 2020; Cheong, 2022).

From the Industry 4.0 in Finance perspective, AI strongly influences digital financial inclusion in areas related to risk detection, measurement and management, addressing the problem of information asymmetry, and availing customer support and helpdesk through chatbots, fraud detection, and cybersecurity. In Malaysian banking services, AI reduces costs, mitigates risk, detects fraud and increases customer satisfaction and loyalty. It further suggests that digital smart contracts can effectively replace traditional paper contracts, facilitating a more credible transaction without jeopardising authenticity and credibility. AI applications for predicting customer loyalty will provide a better understanding of Islamic banking related to customer loyalty and offer a platform that helps bank management improve customer loyalty within Malaysian Islamic banks. Driven by these factors, AI in finance studies attracts widespread interest, particularly in association with FinTech and Islamic Finance (Mhlanga, 2020; Kochhar et al., 2019; Rahman et al., 2021).

Fintech has a tremendous potential impact on conventional and Islamic finance industries. This potential impact on the potential of introducing new business models can bring more transparency and efficiency to the products. It can provide more customer-friendly Islamic financial products and services. The integration of FinTech solutions in the business models took place with the Investment Account Platform (IAP) launch in 2015, the first multi-bank online platform that combines Islamic banks' credit evaluation expertise and the power of technology to allocate funds from investors to economic ventures. More than 300 Fintech start-ups have emerged in the South East Asia region, providing solutions in payments, micro and peer-to-peer lending, and wealth management, which embed AI technologies into their products will make them formidable competitors that create value for customers (Zain et al., 2020; Ali et al., 2019).

AI and machine learning are essential for treasury management. Machine learning prediction models can help predict cash flow. Accuracy in prediction through these machine learning models can protect organisations from various crises and risks. In the banking sector, machine learning predictive models can help to ascertain the borrower's repayment capability and loan approval decision-making will be helpful to the bank in utilising the cash in a way that can be profitable (Donepudi et al., 2020). With the normalisation of smartphones as the primary communication device, mobile banking, a technology-based financial service, has become the new norm of modern banking, which enables banks to offer AI-enabled mobile banking, a mobile banking service using AI and interaction-based algorithms. The banking service is gaining popularity among bank clients, especially young customers such as millennials. Service quality, attitude towards AI and trust are determinants important for millennial loyalty towards AI-enabled mobile banking and further highlight the significant role of religiosity on millennial loyalty towards mobile banking services in Islamic nations (Owusu Kwateng et al., 2019; Suhartanto et al., 2022).

Malaysia is well-known for its leading banking framework in Islamic Finance. The Islamic finance industry's acceptance of AI technology investment is crucial for Islamic financial growth in Malaysia. It is further suggested the positive impact of Text Mining, Algorithmic Trading, Stock Pick, and Robo in Islamic investment systems based on the application of AI in Islamic investment to help consumers make better decisions in Shariah-compliant stocks investment as AI can provide a high-quality service in the investment system. Malaysia is known for its pioneer in the Sukuk market as the alternative to the conventional bond market. AI application on the Sukuk market has given rise to an issue of the availability and accuracy of some of Suku issuance's ratings. Neural network methods (AI) obtain the highest accuracy rate when predicting the actual rating in the market, which suggest AI application is beneficial to the rating agencies, Sukuk issuer companies, corporate managers, private and institutional investor to support their investment decision-making (Gazali et al., 2020)

Parallel to the industrial technology movement, technology adoption is apparent among Malaysian Zakat institutions. Zakat is one of the Islamic pillars. The aim is to solve an economic problem in society through wealth sharing between the rich and the poor according to rules set in the Quran and also guidelines prepared by Muslims, which is under the purview of the State Islamic Religious Council. It is highlighted that the majority of the institutions are lacking in technology adoption, which has been widely adopted throughout the world, especially in the utilisation of mobile technology platforms to reach the public, both the zakat contributor and the recipients (Salleh & Chowdhury, 2020).

Money laundering is a criminal activity used to disguise the source of illegally obtained money and make it appear legitimate in the system (Kute et al., 2021). Despite the increased number of reported money laundering cases in Malaysia, investigation outcomes, either in prosecution, conviction, or confiscation, remain low and ineffective in deterring money laundering activities (Zolkaflil, 2021). While AI applications support the commercial aspect of the finance industry, it is also relevant in the battle against money laundering.

However, identifying suspicious money laundering transactions remains challenging primarily due to the continuously changing canvas of fraud, technology and regulations, being a multi-step classification problem, the challenges around the data for research and barriers to the adoption of AI by industry. Law enforcement and regulatory bodies nowadays employ a robust end-to-end framework utilising AI, which accurately detects suspicious money laundering transactions by reducing the false positives and generating a human interpretable explanation for the decisions made by AI (Kute et al., 2021).

Malaysian Financial Services Legal Framework

At the point of this study, the financial services legal framework is based on Bank Negara Malaysia (BNM) is the regulatory body that governs the financial service industry and regulates the application of FinTech in Islamic Finance in Malaysia under the law provision of the Central Bank of Malaysia Act 2009 (CBMA), the Anti Money Laundering, Anti-Terrorism Financing and Proceeds of Unlawful Activities Act 2001 (AMLATF) and the Islamic Financial Services Act 2013 (IFSA).

The Financial Technology (FinTech) Regulatory Sandbox Framework is introduced to facilitate Fintech innovation to be deployed and tested in a live environment within specified parameters and timeframes, which applies to financial institutions and a FinTech company which collaborates with a financial institution which its business registered under Financial Services Act (FSA) or Islamic Financial Services Act (IFSA) 2013 or a money services business as defined in the Money Services Business Act 2011 (MBSA).

Under the provision of FSA and IFSA, BNM has occasionally issued guidelines to banking and financial institutions to enhance and strengthen security measures undertaken by all participating institutions. Minimum Guidelines on the Provisions of Internet Banking Services by Licensed Banking Institutions issued by the BNM sets the minimum guidelines that licensed institutions in Malaysia should observe in providing Internet banking, and it further provides that banking institutions are free to adopt more stringent measures and are expected to keep up-to-date with technological developments and needs of the customers.

Even though digital currencies are not recognized as legal tender in Malaysia, the Anti-Money Laundering and Counter Financing of Terrorism Policy (AML/CFT) – Digital Currencies (Sector 6) states the minimum requirements and standards that a reporting institution must observe to increase the transparency of activities relating to digital currencies and ensure effective AML/CFT control measures are put in place to mitigate risks that reporting institutions may be used as conduits for illegal activities. While the Anti-Money Laundering, Anti-Terrorism Financing and Proceeds of Unlawful Activities Act 2001 (AMLATF) remain silent on its application to FinTech, the provisions relating to non-compliance are relevant to regulate FinTech-based activities in the Islamic finance industry in Malaysia on reporting obligations of reporting institutions, the penalties of committing the offence and the enforcement authority over any volitation and offences.

Personal Data Protection (PDPA) 2010 aims to regulate the processing of personal data in commercial transactions. It requires entities within eleven industries, including banking and financial institutions, to register with the Personal Data Protection Commissioner. An essential element in discussing the applicability of PDPA is that the provision only applies to processing personal data in respect of commercial transactions, which exempts any personal data processed for non-commercial or private use from this legislation. It also excludes credit reporting under the purview of the Credit Rating Agency Act 2010. BNM is exercising its powers under the Central Bank of Malaysia Act 2009 and other relevant legislation. They are closely monitoring the financial sector's operations in Malaysia to maintain the confidence of the public and investors that the law protects their data and privacy.

The Digital Signature Act 1997 (DSA) outlines the regulatory structure for entities creating digital signatures and legalising private and public key cryptography. The DSA allows individuals and businesses to use digital signatures in commercial transactions. It provides for the licensing and regulations of Certification Authorities, which issue digital signatures and certify the identities of the signatories by issuing a certificate. Digital signature technology offers data security, which encryption algorithms and protocols ensure. Encryption scrambles the data, so it is practically impossible to decipher it without knowing the decryption key. VISA and MasterCard have introduced a standard known as Secure Electronic Transaction (SET) for sending online credit card numbers to purchase goods or services in a safe and secure environment.

The Computer Crimes Act 1997 (CCA) deals with offences relating to the misuse of computers and provides that the commission of the crimes is extra-territorial. The Act also includes an offence involving fraud or dishonesty or which causes injury as defined in the Penal Code, causes unauthorised modification of the contents of any computer and communicates directly or indirectly a number, code, password or other means of access to a computer to any person other than a person to whom he is duly authorised to communicate. It sets out a framework that defines essential terms such as proper illegal access, interception and computer use, outlines the standard for service providers and imposes potential penalties for infringement.

METHODOLOGY

The qualitative method is chosen for this study due to the appropriate process of collecting the data to identify and analyse the issue or problem under the analysis. The qualitative research methodology includes four steps: developing a research plan, acquiring data, analysing data, and producing reports. This comprehensive evaluation of the pertinent literature consists of a narrative synthesis. Via academic writing, narrative synthesis aims to summarise and clarify the synthesis results. Content analysis is a qualitative technique that employs verbal, visual, or written data to systematically and objectively describe a given phenomenon (Jaipong et al., 2023). Content analysis facilitates the development of credible findings. In addition, it is a flexible data analysis technique that can be applied to systematic qualitative reviews. When conducting periodic qualitative evaluations, content analysis methods must be modified or adapted to be compatible with highly organised and contextualised information to locate knowledge and theory. In conclusion, qualitative content analysis was utilised in the current study (Limna et al., 2022; Limna & Kraiwanit, 2022).

RESULTS

Challenges and Concerns

As AI forms one of the critical elements in Industry 4.0, Malaysia has reported a sluggish adoption rate of Industry 4.0, with only 15% to 20% of businesses embracing it (Cheong, 2022). While the benefits and motivations for adopting AI are well-documented, implementing AI technologies can present significant challenges for government and organisations as the scope and depth of potential applications increases and the use of AI becomes more mainstream in Malaysia's context - Institutional, Economic and Social.

Institutional Challenges

An institutional challenge, perhaps, is one of the biggest challenges in AI adoption, given the rapid growth and technological evolution. Data challenges of using AI are validating the benefits of AI solutions and obtaining statistically significant outcome data on transparency and reproducibility in the context of acceptability relating to public perception. The current position on standards and data structures can hinder AI applications regarding data use and integrity (Wamba-Taguimdje et al., 2020; Sun & Medaglia, 2019). The challenges of implementing AI from an institutional perspective require a more holistic understanding of the range and impact of AI-based applications and the concept of AI law and regulations for proper governance, including autonomous intelligence systems, responsibility and accountability, as well as privacy/safety (Wachter & Mittelstadt, 2019; Gupta & Kumari, 2017; Zatarain, 2017).

Despite the legal framework's existence, Malaysia's general public exhibits a lack of trust and concern, given the rising situation of several data breaches and scandals regarding AI adoption in recent years. Issues relating to the ethical dimensions of AI systems and their use of shared data remain unclear regarding ethical and legal concerns, especially around the responsibility and analysis of AI-based systems' decisions (Sun & Medaglia, 2019).

The absence of adequate regulatory requirements, data privacy and security, and lack of relevant skills and IT infrastructure are significant challenges to AI adoption (Rahman et al., 2021). A complete framework of policies, regulations and ethical guidance to prevent the misuse of AI is critical to be developed and enforced by regulators (Duan et al., 2019). AI-based systems may exhibit levels of discrimination even though the decisions do not involve humans in the loop, highlighting the criticality of AI algorithm transparency (Bostrom & Yudkowsky, 2011).

Cyber, physical and political threats arise with the growth in AI. From a banking perspective, precautions should be taken while implementing it, as there is always a threat of leakage of data, which could incur a massive loss to the banks as complete transparency while venturing into new AI projects could lead to leakage of data and misuse of the information (Kochhar et al., 2019). Cybercriminals use technology to launch more sophisticated attacks on organisations. Hence, AI is becoming increasingly crucial in cybersecurity as AI-based products detect risks and secure systems and data. Data protection and privacy issues arise using AI technology (Kamaruddin et al., 2023). For instance, the financial services industry has been reported to have one of the highest rates of insider data breaches despite typically having practical workforce training on cybersecurity best practices (Birruntha, 2023). Due to their dealings with large amounts of sensitive data and personally identifiable information, they are prime targets for attackers. Banks and other financial institutions, ranging from brokerages and investment management firms to credit unions and credit card processors, faced significant security, operational and compliance challenges.

Issues

Despite the Personal Data Protection Act 2010, Malaysia continues to experience profound personal data breach incidents in recent years. In 2022, Communications and Digital Minister Fahmi Fadzil instructed Cybersecurity Malaysia (CSM) and the Department of Personal Data Protection (JPDP) to investigate the alleged data leakage involving 13 million Malaysians that was spread on social media in December 2022, which the leakage was severe as it involved a large amount of Malaysians' private information such as the username, their full name, date of birth, address and identity card number.

Economic Challenges

The mass introduction of AI technologies could have a significant economic impact on organisations and institutions in the context of required investment and changes to working practices. It is focused on the affordability of technology within the medical field, arguing that AI will likely require a substantial financial investment (Dwivedi, 2019; Tizhoosh & Pantanowitz, 2018) While AI advocates productivity improvement, it can also exacerbate economic inequality that could widen the gap between large and small firms, emerging and developed markets, and the rich and poor. Big Data and AI technologies commonly require substantial investment, which implies having scale effects that favour large firms and industry leaders, given their availability of resources. AI adoption increases productivity, but only for large firms. Hence, these firms can become so productive that laggards become discouraged and can never compete ((Mihet & Philippon, 2019; Bughin et al., 2018. Bäck et al., 2022)

AI applications tend to reduce human interaction, which saw its relevance during the COVID-19 Pandemic social distance phase. The direct interaction between the customer and the bank representative reduces customer loyalty. Banks have a particular emotional value with their customers. With the loss of the human touch and the high implementation of AI in the banking sector, customers' loyalty towards their particular bank can be reduced (Kochhar et al., 2019) Malaysian financial institutions have generally embraced AI-embedded Fintech adoption into the business norm. Nevertheless, the study showed that Islamic financial institutions still show some passivity in responding to the growth of Fintech despite realising the potential impact Fintech may have on the Islamic financial industry (Ali et al., 2019).

Social Challenges

Social challenges have been highlighted as one of the main barriers to the further adoption of AI technologies. The increasing use of AI will likely challenge cultural norms and act as a potential barrier within specific population sectors. Culture is a crucial barrier to AI adoption, as people may be reluctant to interact with new technologies and systems. Social challenges include unrealistic expectations towards AI technology and insufficient knowledge of its values and advantages of AI technologies (Dwivedi, 2019; Sun & Medaglia, 2019). The adoption of mobile banking has been sluggish among the senior population in Malaysia. This study revealed the negative influence of dispositional resistance to change and the positive impacts of performance expectancy, effort expectancy, social influence, facilitating condition and hedonic motivation on seniors' intention to adopt mobile banking (Andalib Touchaei & Hazarina Hashim, 2023) The potential job losses due to AI technologies are another aspect of social challenges frequently published and debated in the media and forums. AI creates challenges for humans that can affect the nature of work and potentially influence people's status as participants in society. Perception and fear of Job security influence the adoption of AI technologies. People with jobs involving lots of personal interaction are less likely to be concerned about losing their jobs because of AI adoption (Dwivedi, 2019; Risse, 2019; Coupe, 2019; Bhargava et al., 2021). In the financial services sector, banks face the risk of backlash from their employees due to the potential automation of tasks, which can result in job loss and job reassignments and could lead to possible dissatisfaction among employees, resulting in resignations or employees being fired due to inefficiency (Kochhar et al., 2019).

DISCUSSIONS

In summary, AI's progression towards becoming the next general-purpose technology in Malaysia's finance industry is consistent with the global trend. Specific sectors within the industry have yet to embrace the technology entirely. While reservations remain in certain quarters of the industry, it is undeniable that its application has significantly impacted the new social-economic norms, especially during the COVID-19 Pandemic (Boukherouaa et al., 2021). While AI Adoption in Malaysia's Finance Industry is not yet ready to replace human interactions, the findings support the general notion that AI adoption in the finance industry improves productivity, enriches job functions, and enhances the level of services and customer experience, translating into better performance.

It also supports Kamaruddin et al. (2023) that because of the significant importance of the finance industry in the economic system, the institution must examine citizen data protection and privacy concerns and re-examine its governance, including legal, regulatory and enforcement mechanisms to see if it conforms to international practice and consider reforms where is deem necessary given the increasing incidents of data breach.

According to Liu et al. (2021), as AI-based privacy invasion attacks are challenging to defend against due to the sophisticated capability of state-of-the-art ML methods in extracting personal information, privacy in some contexts is not apparent and privacy threats from organisations and government sectors that collect and analyse data on a large scale.

AI adoption in the financial sector supports that given AI's rapid and exponential growth, measures need to be taken to create a healthy growth environment to harness the benefits of AI adoptions. At the same time, mitigate the challenges and concerns surrounding it. Both institutions and implementing stakeholders play an essential role in addressing the circumstances in view that society generally is yet to fully grasp many of the ethical and economic considerations associated with AI and big data and its broader impact on human life, culture, sustainability and technological transformation. Therefore, a governance framework is required to prevent ML algorithms from automatically mining private information, intentionally or unintentionally. From the implementing stakeholders, a more robust security strategy is needed to regulate employees' access to prevent employees from intentionally or unintentionally facilitating fraudulent activities by unauthorised access or information to scammers. These measures are vital to restoring public trust and encouraging a more progressive and sustainable adoption of AI in Malaysia. While AI offers numerous disruptive opportunities in the Financial Technology (FinTech) industry regarding data acquisition, analysis, protection, and process streamlining, it also poses threats and concerns to incumbent industry stakeholders. This study provides policymakers and industry stakeholders with crucial insights for addressing AI's challenges. It is the first study to examine the significance and prospective challenges of implementing AI technology in Malaysia's financial sector.

CONCLUSIONS

The development of AI as a general-purpose technology in Malaysia's financial sector is consistent with the global trend. However, not all sectors of the industry have entirely adopted AI yet. The implementation of AI has had a significant impact on socio economic norms, particularly during the COVID-19 pandemic. While AI adoption is not yet ready to replace human interactions, it has been found to boost productivity, improve job functions, and improve consumer experiences in the finance sector. It is necessary to foster a healthy growth environment to maximise the benefits of AI adoption while mitigating obstacles and concerns. Institutions and implementing constituents have a role in addressing the ethical, economic, and societal problems associated with AI and big data. Due to its importance in the financial system, the finance industry must investigate data protection and privacy concerns, review governance practices, and consider any necessary reforms to conform to international standards. As AI-based privacy invasion assaults are challenging to defend against, a governance framework is required to prevent unintentional or intentional extraction of personal data by ML algorithms. Stakeholders should implement robust security strategies to regulate employee access and prevent unauthorised access or information sharing that could aid in fraudulent activities. These measures are essential for restoring public confidence and assuring AI's progressive and long-term adoption in Malaysia's financial sector. This study proposes future research directions to resolve the institutional framework's limitations on data privacy and AI adoption in Malaysian SMEs. The institutions should prioritise data privacy and protection by scrutinising and enhancing their governance frameworks, including legal, regulatory, and enforcement mechanisms, following international standards. Implementing robust security measures to regulate employee access and prevent unauthorised activities that may facilitate fraud is essential. It can help maintain the integrity and credibility of the financial industry. The public should be educated and aware of artificial intelligence's ethical and economic implications to promote a more informed and responsible adoption of AI to ensure a sustainable and equitable approach. Collaboration between industry stakeholders, policymakers, and academia should be encouraged to establish guidelines, standards, and best practices for AI adoption in the finance industry. Future research should focus on addressing the limitations of the institutional framework regarding data privacy and AI adoption in small and medium-sized enterprises (SMEs) in Malaysia, given the importance of these businesses to the economy of the country. By implementing these recommendations, Malaysia's finance industry will be able to navigate the challenges associated with AI adoption, safeguard data privacy, and foster responsible and sustainable growth in the AI era.

The limitation of this study is that it is a review article. Therefore, the quantitative and qualitative approaches, such as interviews and questionnaires from respondents, could give more insight into further research.

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A Review of Sustainable Development Guidelines for Green Universities in Thailand

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ABSTRACT

Objective: This article presents important content about Guidelines for Sustainable Green University Development in Thailand, Higher Education Institution Under the Ministry of Higher Education, Science, Research, and Innovation, there are 171 agencies. Receive government policy according to the 20-year national strategy (2018–2027), the National Economic and Social Development Plan No. 13 (2023–2027), and government policies to solve climate problems. The goal is to achieve carbon neutrality by 2050 and net greenhouse gas emissions of zero.

Methodology: This article was reviewed, and the writing employed a systematic review adopting theories based on sustainable development integrated with business into educational sectors. The scholarly papers were from valid sources like Google Scholar, Scopus and Web of Science databases. The research strategy is a qualitative approach using content analysis that was analysed by four researchers with business and education backgrounds.

Results: The UI Green Metric World University Rankings are a globally accepted benchmark demonstrating a university's commitment to environmentally friendly management and sustainable development. It is a challenge for higher education institutions and administrators in Thailand to responsibly create public awareness of environmentally friendly activities towards the world, which is the goal of sustainable development (Sustainable Development Goals; SDGs). Participating universities in the UI Green Metric World University Ranking helps promote internationalisation and recognition efforts.

Conclusions and Recommendations: This article proposed the guidelines for developing sustainable green universities in Thailand's Green Metric World University Rankings. It should be promoted to provide opportunities for developing sustainable green universities in Thailand. The recommendation for further study is to consider questionnaires or interviews with respondents for more comprehensive data results and continue research on green universities that could apply to universities worldwide.

Keywords: *Sustainable Development, Green, Universities, Carbon Neutrality, Metric*

INTRODUCTION

Currently, the concept of a green university is spreading throughout the world. Based on sustainability and social responsibility, the university mainly focuses on protecting the environment. It is a critical mission that the university must give importance to. Being a place of learning where many instructors, students, and staff from different fields come together to conduct educational activities, Universities also play a significant part in community and stakeholder collaborations to tackle climate change. We encourage energy and water conservation by fostering new concepts and innovations, including waste recycling, environmentally friendly transportation, behavioural modifications, and economic and social challenges associated with sustainability. The university will provide an excellent example for the community and support government environmental policy (Wright, 2010).

The Brundtland Report described sustainable development as "that meets the needs of the present without hurting the ability of future generations to meet their own needs." (United

Nations,1987). Almost 140 developing countries worldwide are looking for ways to meet their development needs. However, with climate change becoming a bigger problem, actual steps.

The UI GreenMetric World University classification is based on green campuses and environmental sustainability. The UI GreenMetric World University Rankings prudently ranked universities based on ecological commitment and initiatives using 39 indicators across six criteria. Universities play a crucial role in the joint endeavour of stakeholders and communities to combat climate change. Universities will promote energy and water conservation, waste recycling, and green transport by promoting and developing novel concepts and innovations. However, such activities will necessitate a change of behaviour and economic and social problems related to sustainability. In this regard, universities will serve as a model for society and a vital government partner. Initially, quantitative data from universities is acquired and transformed into a single score reflecting the institution's efforts to implement environmentally friendly and sustainable programmes. This score will be used to rate universities. The rankings will be helpful to university leaders in their efforts to implement eco-friendly policies and manage behavioural change within their respective academic communities. The vision is to be an open and reputable World University Ranking that has lasting effects on universities worldwide. The objectives are: (1) sustainability-based World University Rankings are compiled annually, (2) promoting sustainability practices in universities worldwide, (3) delivering services related to sustainability to universities around the globe, and (4) facilitating international sustainability partnerships. There are university collaborations in sustainability. The United States Green Report Card is a ranking system integrating sustainability for 300 universities. However, the results are presented as letter grades (A to F) rather than rankings, and the number of featured universities is limited (Atici et al., 2021; UI GreenMetric, 2023).

In 2014, 15 universities in Thailand joined the UI Green Metric World University Ranking. In 2022, 47 universities in Thailand joined the UI Green Metric World University Ranking out of 1,050 participating universities worldwide. Currently, 2023 has changed the new evaluation criteria to 72 indicators. The six criteria are: 1) Setting and Infrastructure (SI), 2) Energy and Climate Change (EC), 3) Waste Management (WS), 4) Water Management (WR), 5) Access and Mobility (TR) and 6) Governance (GV).

1. Setting and Infrastructure (16%)
Green open space and facilities are available to the community in the municipality or city.
2. Energy and Climate Change (19%)
Increase the use of energy-efficient equipment and develop renewable energy.
3. Waste Management (19%)
Several policies and programs to reduce
4. Water Management (15%)
Reducing the use of groundwater, increasing conservation programs and using clean and proper water

5. Access and Mobility (16%)
Policies to limit the use of emission private vehicle
6. Governance (15%)
Budget, program and community participation in the field of sustainability
(Universitas Indonesia, 2023)

In Thailand, there is awareness of environmental issues among society and global trends in sustainable development and global warming. It is a problem that affects the lives of people in society all over the world and is becoming more and more severe day by day due to the production of greenhouse gases in the atmosphere, which causes greenhouse gases. It comes from the activities and behaviours of human life. The "Green Office" project of the Department of Environmental Quality Promotion was born to promote production and environmentally friendly consumption by developing environmental standards known as G-Green standards. To cover producer groups and service providers in many sectors of Thai society, including training and knowledge In the Green Office project for private agencies, government agencies and universities. to promote production and environmentally friendly consumption by developing environmental standards, known as G-Green standards, to cover producer groups and service providers in many sectors of Thai society, including training and knowledge In the Green Office project for private agencies, Government agencies and universities.

In 2021, there were 170 universities (Department of Environmental Quality Promotion, Ministry of Natural Resources and Environment, 2021). For universities, participation in the UI Green Metric World University Ranking helps promote efforts. It will make the university international and be accepted in many countries. Participation in the UI Green Metric rankings also helps increase university website traffic. References and links to institutions dealing with sustainability issues are available on web pages, which also helps increase contacts with institutions interested in your university. Importantly, there is a lack of research on steps to prepare for green university development in Thailand.

Research Question

How can sustainable development help reduce global warming?

Research Objective

This study proposes guidelines for the sustainable development of green universities in Thailand. These guidelines aim to increase environmental sustainability and raise awareness of global warming. As a result, universities in Thailand are becoming greener and gaining recognition in many countries.

LITERATURE REVIEW

Green Office Concept

Principles and reasons "Green Office" in Thailand is about creating awareness among citizens to carry out environmentally friendly activities responsibly towards the world, which is the goal of sustainable development (Sustainable Development Goals; SDGs), a green office, and various activities within the office that have the most negligible impact on the environment by 1) using resources and energy wisely 2) managing waste efficiently 3) Selecting materials, equipment, and office supplies that are environmentally friendly 4) Low greenhouse gas emissions.

In addition, offices that can participate in the Green Office project are private agencies. Government agencies and educational institutions In terms of the scope of the office, it is inside and outside the building. People who work or have professions use the office to work on documents, meetings, and exhibitions. Including other usable areas inside, such as dining areas. Cooking area, parking lot, bathroom, and waste treatment system.

Green Office Criteria: Six Categories (100 points) as follows:

Category 1: Policy determination Plan operations and continuous improvement. (25 points)
- 1.1 Environmental policy making
- 1.2 Working Group for the Environment
- 1.3 Identifying resource issues and the environment.
- 1.4 Related laws and regulations
- 1.5 Greenhouse gas information
- 1.6 Plans for projects that lead to improvements all the time
- 1.7 Green office assessment within the office (for agencies that request renewal and upgrade)
- 1.8 Review by management

Category 2: Communication and awareness creation (15 points)
- 2.1 Training to provide knowledge and assessment of understanding
- 2.2 Campaign and public relations for employees

Category 3: Use of resources and energy (15 points)
- 3.1 Water use
- 3.2 Power consumption
- 3.3 Use of other resources
- 3.4 Organising meetings and exhibitions

Category 4 waste management (15 points)
  4.1 waste management
  4.2 management of wastewater

Category 5 Environment and safety (15 points)
  5.1 Weather
  5.2 Light
  5.3 Sound
  5.4 Livability
  5.5 Emergency preparedness

Category 6 Purchasing and hiring (15 points)
  6.1 Product Purchasing
  6.2 Hiring

Benefits of the Green Office Project

Participating agencies can cut back on administrative costs. resulting from the economical and efficient utilisation of energy resources

1. The agency has managed an environment that is good for employees' health.
2. It raises the standard of the office to be more environmentally friendly.
3. It helps reduce greenhouse gas emissions. It is part of helping reduce global warming.

Management Guidelines for Green Office

An office in the sense of a green office means a workplace designed and constructed by government agencies, state enterprises, and private companies inside and outside the building. The workers or professionals use it as a place to work on documents. Meetings, exhibitions, and other usable areas within the office, including dining areas. Cooking area, restroom, parking lot, waste receiving area, waste treatment system (Department of Environmental Quality Promotion Ministry of Natural Resources and Environment, 2021)

Green office evaluation consists of 6 categories, 23 issues, and 63 indicators by universities and faculties participating in the green office project. Organised by the Department of Environmental Quality Promotion and Faculty of Environment and Resource Studies, Mahidol University sets guidelines for green office management. Details are as follows:

Figure 1. Green Office Awards in Thailand
(Phuangsuwan, 2019)

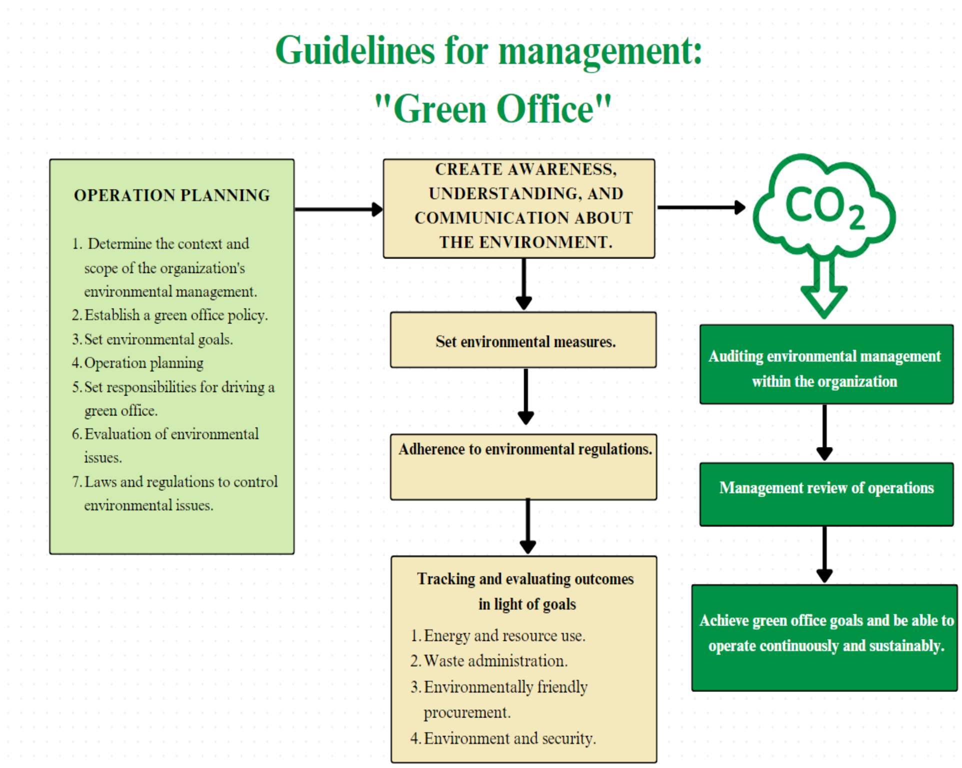

Figure 2. Guidelines for Management "Green Office."
(Aroonsrimorakot & Boonruang, 2023)

RESEARCH METHODOLOGY

In this research, qualitative research methods were used. Qualitative research aims to clarify the context in which individuals or groups make decisions and act in specific ways. It also explains why precisely observed phenomena occur. (Kok, 2023; Lim, 2023; Limna & Kraiwanich, 2022). The researcher collected secondary data from documents, articles, and textbooks, including experiences as a green office auditor. Researchers also participated in the Department of Environmental Promotion Green Office Project, relying on interpretation. Content analysis uses sustainable development, green universities, carbon neutrality, and green metrics. This article was reviewed, and the writing employed a systematic review using theories based on sustainable development integrated with business ino educational sectors. The scholarly articles originated from credible sources such as Google Scholar, Scopus, and Web of Science databases. The research strategy is a qualitative approach employing content analysis, which was analysed by four business and education-trained researchers.

RESULTS

Guidelines for developing sustainable green universities in Thailand by universities in Thailand will join the green office project. Organised by the Department of Environmental Quality Promotion and the Faculty of Environment and Resource Studies at Mahidol University, the Green Office project has been encouraged by government agencies, educational institutions, universities, and private agencies, including various entrepreneurs. In addition, all members set rules, policies, management processes, and the organisation's decision-making. Participation in all sectors, including the division of duties Those responsible for all six categories of green office operations, emphasising participation in activities and follow-up results for the benefit of the public, are considered essential. To create awareness and sustainability, have a better quality of life, including communication and exchanging opinions. Green Office operations should be reviewed by executives, which is consistent with research.

Tiyarattanachai and Hollmann (2016) examined the 'Green-Campus initiative and its impacts on the quality of life of stakeholders in Green and Non-Green Campus universities.' The study investigated how stakeholders' perceived quality of life on their campuses and their satisfaction related to sustainability practices at universities in Thailand with green campuses. The research recommended that universities adopt the standards outlined in the UI Green Metric World University Ranking to promote sustainability on their campuses and enhance the quality of life for all stakeholders. Additionally, at Mahidol University in Thailand, Aroonsrimorakot (2018) proposed the Green Office Management Standard to address and mitigate climate change through adaptable green office solutions. This study underscores the importance of human factors and behavioural patterns in workplaces and offices.

DISCUSSIONS

The results support Zen et al.'s (2016) idea that a participatory-based strategy is in the governance and institutionalisation process of waste minimisation. The process entails the decentralisation of solid waste management, the establishment of co-production of knowledge and co-implementation, and the deployment of effective monitoring. These many components have a significant role in fostering the advancement of sustainable consumption practices and influencing behavioural shifts within the campus community. This study provides a comprehensive analysis of the utilisation of waste profile data derived from research, highlighting its efficacy in enhancing waste management practices for waste minimisation. This study's findings contribute to advancing integrated solid waste management strategies within campus environments. The successful implementation of waste minimisation measures in campus sustainability is demonstrated by scientific evidence that supports a combination of top-down and bottom-up governance approaches.

The finding supports Ong et al. (2021) that the primary obstacles encountered in adopting green office practice encompassed limited financial resources, insufficient knowledge and understanding, a shortage of specialised skills, issues about responsibility and accountability, and considerations related to the physical characteristics of the building. Practitioners and policymakers must enhance the implementation of environmentally sustainable office practices nationwide. The awareness among practitioners and office owners regarding ecologically sustainable practices in office settings. Policymakers should prioritise the advancement of green building development. Additionally, the findings also support Fateye et al. (2023) that the green office is comprised of (1) the utilisation of energy-efficient lights and appliances, (2) alternative sources of power, such as solar power or wind power, (3) the design of landscapes to optimise passive solar energy utilisation (4) the optimisation of spatial utilisation (5) plumbing fixtures designed for water conservation (6) ventilation systems that are engineered to optimise thermal regulation (7) mitigation of adverse impacts on the local ecosystem (8) the practice of adaptive reuse involves repurposing existing buildings for new functions or purposes (9) non-synthetic and non-toxic materials (10) woods that are harvested responsibly (11) wood and stone sourced from the immediate vicinity and (12) The utilisation of reclaimed architectural salvage.

CONCLUSIONS

The term "office" in the context of a green office refers to a professional environment intentionally planned and built by governmental entities, state-owned enterprises, and private corporations within and outside a physical structure. Individuals in various occupations utilise it as a designated space for document-related tasks. The office includes dining facilities, meeting rooms, exhibition places, and other functional zones. The facilities provided in the establishment include a designated space for food preparation, sanitary facilities for personal hygiene, a designated area for vehicle parking, a designated room for the collection of waste materials, and a system in place for waste treatment. The success of the green office policy It arises from the completion of the process in the six categories of green office evaluation criteria of the Department of Environmental Quality Promotion and the Faculty of Environment and Resource Studies at Mahidol University, namely Category 1: policy determination, plan operations, and continuous improvement. Category 2: Communication and awareness creation Category 3: Use of resources and energy Category 4: waste management Category 5: Environment and Safety, and Category 6: Purchasing and Hiring. Factors that cause the operation's success depend on the level of cooperation of those who adopt the green office policy. There is a high level of collaboration and results from implementing the green office policy. It is consistent with the duties and mission of the agency. They must be aware of problems, obstacles, and solutions to policy implementation and the path to success in driving it. Green office policy.

LIMITATION AND RECOMMENDATION

This research is a review article. It may not include respondents in this study. The researchers recommend continuing quantitative and qualitative analyses in further analysis for comprehensive results. Thus, green university development in Thailand should be based on research and development.

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Predicting Electricity Consumption at La Trobe University Using Machine Learning Algorithms

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ABSTRACT

Objective: This study aims to predict and optimise electricity consumption patterns at La Trobe University's Bundoora Campus from 2018 to 2021. The research involves rigorous feature extraction and model evaluation using the UNICON dataset.

Method: This study employs machine learning algorithms, including Random Forest, CatBoost, and XGBoost, to predict and optimise electricity consumption. The methodology adopted in this study is designed as a multi-step, iterative process to construct a highly accurate and robust predictive model for electricity consumption.

Result: Achieving an R^2 value of 0.99 with a stacked model. The study not only shows high predictive accuracy but also offers practical, cost-saving recommendations, particularly in HVAC tuning and demonstrates the model's utility for real-world energy management.

Conclusion: We have comprehensively evaluated the performance of multiple machine learning algorithms in predicting building electricity consumption. By analysing the discrepancies between predicted and actual consumption, facility managers can gain valuable insights into building performance, thereby allowing for more targeted energy-saving interventions.

Recommendation & Implication: Not only does the study show high predictive accuracy, but it also offers practical, cost-saving recommendations, particularly in HVAC tuning, and demonstrates the model's utility for real-world energy management. The findings contribute to achieving Net Zero Carbon Emissions by 2029 at La Trobe University. Although the study focuses on one campus, the methodology has broader implications which can be applied to other institutions.

Keywords: *Electricity Consumption, Energy Optimization, Academic Institutions, Machine Learning, Ensemble Method, Net Zero Carbon Emissions*

INTRODUCTION

La Trobe University's Bundoora Campus has committed to achieving Net Zero Carbon Emissions by 2029 (Chen et al., 2023). This paper presents a case study analysing the campus's electricity consumption patterns from 2018 to 2021 (Moraliyage et al., 2022), a period marked by the extraordinary circumstances of the COVID-19 pandemic, which led to unprecedented shifts in energy use. La Trobe University has established the La Trobe Energy Artificial Intelligence (AI)/Analytics Platform (LEAP) to support its sustainability targets. This platform employs AI and Data Analytics to scrutinise, forecast, and enhance electricity utilisation, aligning with the institution's sustainability commitments (Ewis et al., 2023).

This study aims to augment LEAP using an advanced machine learning-based predictive model (Panos et al., 2023) and utilising the extensive UNICON dataset (UNICON Energy Consumption Dataset, 2022)), which records electricity consumption in campus buildings. Our research introduces a multifaceted approach to understanding electricity consumption by accounting for various factors, from temporal patterns to building-specific characteristics. It allows us to forecast consumption with high precision and offer actionable energy optimisation recommendations. The study yielded vital insights into the relationships between different factors and electricity consumption, ultimately aiding in identifying consumption patterns that could result in significant cost savings and sustainability benefits. Although focused on a single campus, the methodologies and findings of this research have broader applicability and could be extended to other academic institutions (Aniegbunem & Kraj, 2023).

LITERATURE REVIEW

Energy Consumption in Academic Institutions

The importance of energy management in academic institutions has been well-documented in the literature. Studies such as those by Lin-Rui et al. (2021) and Vour-doubas (2019) provide a foundational understanding of the complexities of managing energy consumption in educational settings. These works set the stage for our research at La Trobe University and highlight the need for a holistic approach to energy management, considering factors like thermal comfort and carbon emissions (Lin-Rui et al., 2021; Vourdoubas, 2019). Kuswanto (2022) extended this narrative by exploring how institutional services can impact overall consumption patterns, including energy management. These collective insights underscore the relevance of our research focused on La Trobe University and serve as a segue into the methodologies employed in our study. Additionally, a systematic review by Ardabili et al. (2022) emphasises the role of machine learning and deep learning in building energy systems, further validating the need for advanced predictive models in academic institutions.

Feature Importance, ML Algorithms, and Evaluation Metrics

The accuracy of predictive models in energy management is heavily influenced by feature selection and extraction, a point that has been rigorously emphasised by Ayub et al. (2020). Their work is a cornerstone in understanding the importance of selecting the correct variables and features for machine learning models, which is crucial for achieving high predictive accuracy. In the realm of machine learning algorithms, Random Forest, CatBoost, and XGBoost have emerged as frontrunners due to their robustness and high predictive accuracy across a variety of domains, including energy management (Bochenek & Ustrnul, 2022; Sahin, 2020; Alshboul et al., 2022). Among these, the work by Khan et al. (2020) stands out for its specific focus on the CatBoost algorithm. They propose a hybrid machine learning approach that integrates multilayer perceptron (MLP), support vector regression (SVR), and CatBoost for power forecasting. This multi-algorithmic approach validates the robustness of CatBoost and high predictive accuracy, making it particularly relevant to our study. Evaluation metrics are another cornerstone in the realm of predictive modelling. Metrics such as RMSE and R^2 are widely accepted standards for assessing the performance of predictive models (Moayedi & Mosavi, 2021; Lee et al., 2021). In this context, the works of Cai et al. (2019) and Geng et al. (2020) offer additional layers of complexity and utility. Cai et al. delve into the intricacies of predicting energy consumption in residential buildings, emphasising the critical role of accurate prediction models for effective supply-side and demand-side energy management. Geng et al. extend this narrative by introducing economic considerations, explicitly focusing on cost-effective energy consumption strategies under time-of-use electricity tariffs.

Practical Implications and Sustainability Goals

While predictive accuracy is crucial, the literature emphasises the need for practical applications and broader sustainability goals. Liu et al. (2019) and Aram et al. (2022) go beyond mere prediction to discuss the real-world implications of their models, offering invaluable insights for facility management and long-term sustainability initiatives. These studies align closely with our research, which aims for high predictive accuracy, focuses on the practical implications and contributes to La Trobe University's goal of achieving Net Zero Carbon Emissions by 2029.

RESEARCH METHODOLOGY

The methodology adopted in this study is designed as a multi-step, iterative process to construct a highly accurate and robust predictive model for electricity consumption. As illustrated in Figure 1, the workflow comprises the following stages: Data Collection, Data Preprocessing, Feature Extraction, Model Training, Model evaluation, and Prediction. One distinguishing feature of this methodology is that it includes a conditional loop for model optimisation. After each model training and evaluation iteration, the process loops back to the Feature Extraction stage if the model fails to meet predefined accuracy threshold criteria, specifically the coefficient of determination $R^2 > 0.95$. This iterative approach allows for the fine-tuning of features, intending to enhance model accuracy until peak performance is achieved. This approach ensures that the predictive model is accurate and robust, meeting the rigorous demands of real-world applications in electricity consumption forecasting.

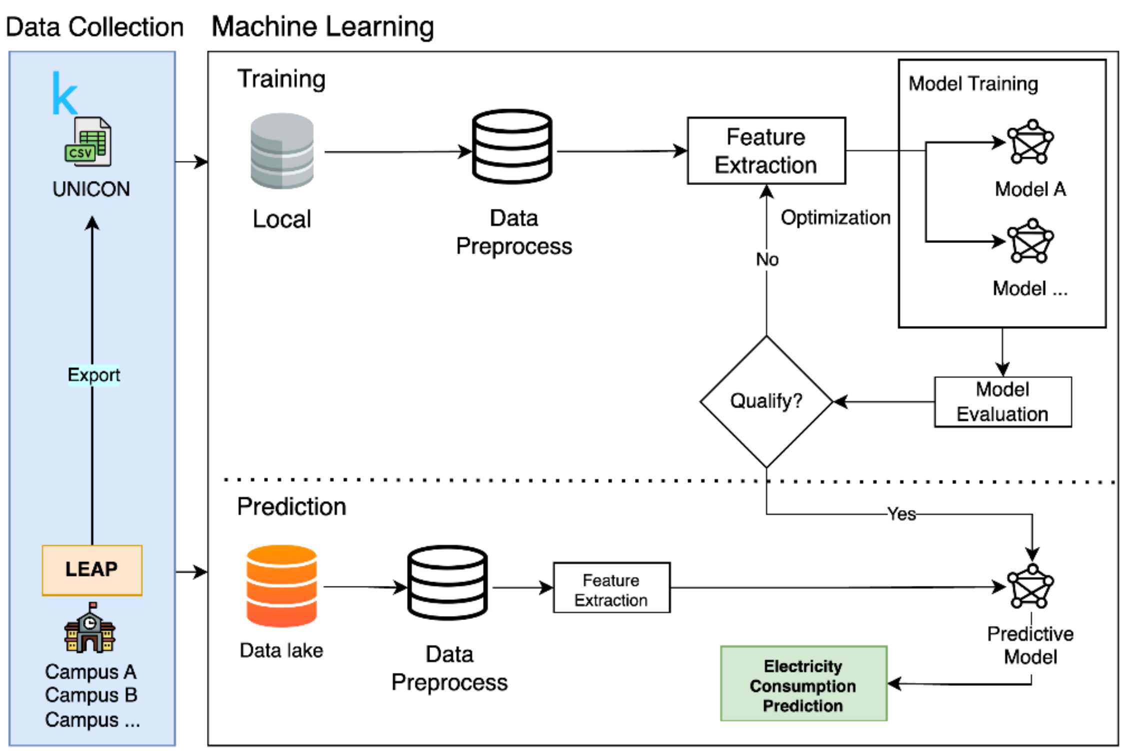

Figure. 1. Overview of the Multi-Step, Iterative Workflow for Electricity Consumption Prediction

Data Collection

The initial phase of our methodology is data collection. The raw data from Kaggle originates from the La Trobe Energy AI/Analytics Platform (LEAP). The original dataset is extensive, comprising multiple CSV files that include metrics related to energy consumption - specifically, electricity, gas, and water. However, this study focuses exclusively on electricity consumption.

Table 1. List of CSV Files Used in the Study

File Name	Description
building_consumption.csv	Consumption data of buildings
building_meta.csv	Meta information about buildings
events.csv	Dates related to events at the building level
weather_data.csv	Collected weather data
calendar.csv	University calendar for the data collection period

Moreover, while the dataset provides information on various events that could affect electricity consumption, our study focuses on two particular events: the COVID-19 lockdown and HVAC system tuning. These events have the most significant impact on electricity consumption.

The findings noted that the dataset contains information from various La Trobe University campuses and numerous buildings within these campuses. However, we specifically concentrate on the Bundoora Campus and narrow our focus to five buildings affected by the same events (COVID-19 lockdown and HVAC tuning). The dataset provides a comprehensive historical record spanning from 2018 to 2021. By focusing on the specific aspects described above, we aim to construct a robust and accurate predictive model for electricity consumption patterns at selected buildings in the Bundoora Campus.

Data Preprocessing

Following data collection, the subsequent phase is Data Preprocessing. This crucial step cleans and transforms the raw data into a suitable format. This stage involves a series of specific tasks tailored to our dataset and study objectives. Initially, we start with the building_consumption.csv file, filtering the data to include records corresponding to campus_id = 1**,** which identifies the Bundoora Campus. The original file captures electricity consumption data at 15-minute intervals, which we aggregate to daily consumption by taking the mean value for each day.

Subsequently, the building_meta.csv file is used to eliminate buildings with missing data. This cleaned metadata is then merged with the processed consumption data, using building_id as the critical field. Further dataset refinement involves merging it with the events.csv file. We specifically select five buildings affected by COVID-19 lockdowns and HVAC tuning events, using building_id and date as the criteria for merging.

Table 2. The Initial Set of Features and Their Descriptions

Feature	Description	Example Value
built_year	The year the building was built	1967
category	Type of building use	mixed-use
gross_floor_area	The total floor area of the building	145226.2
room_area	Area of the room	2850.78
capacity	Building capacity	1246
event_type	Type of event affecting consumption	HVAC_Tuning
apparent_temperature	Perceived outside temperature	18.54
air_temperature	Actual outside temperature	19.37
dew_point_temperature	Dew point temperature	12.39
relative_humidity	Relative humidity	67.9
is_holiday	Indicator for holidays	1
is_semester	Indicator for academic semesters	0
is_exam	Indicator for exam periods	0
date	Date of data entry	2018-01-01
consumption	Electricity consumption	8.51

The weather_data.csv file, which initially has a 1-minute timestamp interval, is also aggregated to daily levels. The features of wind speed and wind direction are excluded due to their high rates of missing values and weak correlation with electricity consumption.

Finally, we integrate university calendar data from the calendar.csv file, aligning it by date. After completing these preprocessing steps, an initial dataset is obtained, ready for the subsequent phase of Feature Extraction. Suppose the predictive model fails to meet predefined qualification criteria during the evaluation stage; in that case, the methodology reverts to Feature Extraction, as shown in Figure 1, for further refinement and performance improvement.

Feature Extraction

The Feature Extraction phase represents a pivotal step in our methodology, as illustrated in Figure 1. This stage focuses on enriching the dataset by generating new, informative features that are tailored to the predictive model. The following paragraphs elaborate on the specific techniques we applied for feature extraction. Firstly, we introduce a new column, category_id**,** assigning unique integer identifiers to each building category. It simplifies the representation of building types, making it more conducive for model training. Secondly, we manipulate the event_type column, bifurcating it into two binary features: HVAC_tuned and COVID_Period. Both features adopt binary values, with 1 denoting the post-event period and 0 representing the pre-event period. Additionally, we decompose the date column into three separate features to capture better temporal dependencies: year*,* month*,* and day. The month feature undergoes further transformation to align with the Australian seasons and is converted into integer values as season_id**.** Similarly, the day feature is processed into day_of _week and is_weekend to encapsulate weekly patterns. Through these feature transformations, we aim to construct a dataset rich in features that can effectively model the nuances of electricity consumption. It aids in the development of a predictive model that is both robust and accurate.

Table 3. Newly Extracted Features and Their Descriptions

New Feature	Description
category_id	Unique integer values are assigned to each building category.
HVAC_tuned	Binary value indicating (1 for post-event, 0 for pre-event)
COVID_Period	Binary value indicating (1 for post-event, 0 for pre-event)
year	Extracted from the date
month	Extracted from the date
day	Extracted from the date
season_id	Derived from the month and tailored to Australian seasons
day_of_week	Derived from day
is_weekend	Binary value indicating if the day is a weekend (1 for yes, 0 for no)

Model Training

As illustrated in Figure 1, the Model Training phase focuses on developing a predictive model for electricity consumption. In this study, we employ four machine learning algorithms: Random Forest, CatBoost, XGBoost, and a Stacked Model combining the three. These algorithms were selected for their robustness, capability to handle complex data structures, and proven effectiveness in regression tasks.

Random Forest is an ensemble learning method that consists of a collection of decision trees. It is highly flexible and less prone to overfitting, making it suitable for predicting electricity consumption patterns (Sahin, 2020).

The general form of a Random Forest prediction for a given input x is:

$$\hat{y} = \frac{1}{n_{trees}} \sum_{i=1}^{n_{trees}} f_i(\mathrm{x})$$

Where n_{trees} is the number of trees in the forest and f_i (x) is the prediction of the *i-th* tree.

CatBoost (Categorical Boosting) is a gradient-boosting algorithm that excels in handling categorical features without prior preprocessing. It is advantageous in our study as we have several categorical features like category_id and season_id**.**

The prediction of CatBoost for a given input x is:

$$\hat{y} = \sum_{i=1}^{n} \lambda_i f_i(\mathrm{x})$$

n is the number of iterations and λ_i the learning rate for the *i-th* iteration.

XGBoost (Extreme Gradient-Boosting) is another gradient-boosting algorithm known for its high performance and speed (Alshboul et al., 2022). It can handle missing data and is highly customisable, fitting the diverse features in our dataset.

The prediction of XGBoost for a given input x is:

$$\hat{y} = \phi(\mathrm{x}) = \sum_{i=1}^{T} f_t(\mathrm{x})$$

T is the number of boosting rounds and $f_t(\mathrm{x})$ the prediction of the *i-th* boosting round.

A stacked Model is an ensemble method that combines the predictions from multiple machine learning algorithms to improve the model's overall performance (Ayub et al., 2020).

The general form of a stacked regression prediction for a given input x is:

$$\hat{y} = \alpha_1 f_{\mathrm{RF}}(\mathrm{x}) + \alpha_2 f_{\mathrm{CB}}(\mathrm{x}) + \alpha_3 f_{\mathrm{XGB}}(\mathrm{x})$$

Where α_1 α_2 α_3 are the stacking weights, and f_{RF}, f_{CB}, f_{XGB} are the predictions from Random Forest, CatBoost, and XGBoost, respectively?

By employing these algorithms, we aim to construct a robust and accurate predictive model capable of effectively forecasting electricity consumption, fulfilling the requirements for real-world applications in this field.

Model Evaluation

In the Evaluation phase, the performance of the predictive models is rigorously assessed to ensure their reliability and accuracy in forecasting electricity consumption. We employ two evaluation metrics: Root Mean Square Error (RMSE) and the coefficient of determination (R^2).

Root Mean Square Error (RMSE) is a popular regression metric that is beneficial when errors are normally distributed. It offers an interpretable measure in the same unit as the target variable, kilowatt-hours (kWh). It makes it easy to understand the magnitude of the errors regarding actual electricity consumption (Ayub et al., 2020; Moayedi & Mosavi, 2021).

The formula for RMSE is given by:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

y_i $\hat{y}_i$ Where and are the actual and predicted values, respectively, and n is the number of observations.

The Coefficient of Determination (R^2), commonly known as R^2, measures how well the model's predictions match the actual data. An R^2 value close to 1 indicates that the model explains a large proportion of the variance in the dependent variable, which is desirable in our context (Lee et al., 2021; Moayedi & Mosavi, 2021).

The formula for R^2 is:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y}_i)^2}$$

Where y_i is the actual value, $\hat{y}_i$ is the predicted value, y is the mean of the actual values, and n is the number of observations.

Using both RMSE and R^2 allows us to gauge our models' accuracy and explanatory power, ensuring they are fit for practical applications in forecasting electricity consumption.

RESULTS

The work included feature importance analysis, a comparison of algorithms, and a case study on the predictive model's practical implications for different buildings.

Feature Importance Using Random Forest

The importance of the feature was initially determined using the Random Forest algorithm. The Random Forest model provides an in-built attribute to measure the importance of each feature, computed as the average impurity decreases across all trees in the forest (Sahin, 2020). Table 4 lists the features of each important group considered for our experiments.

Table 4. Features Included in Each Important Group

Group	Features
High	category D, room_area, gross_floor_area, HVAC_tuned
Medium-to-High	High+ COVID_Period, is_weekend, day_of_week, built_year, capacity
All Features	All available features

Performance Comparison Across Different Feature Sets

It aims to evaluate the impact of different feature sets on the model's performance; experiments were conducted using three distinct sets of features: High importance, medium-to-high importance, and all features. Table 5 summarises the performance metrics for each feature set.

Table 5. Performance Metrics Across Different Feature Sets Using Random Forest

Feature Set	RMSE (kWh)	R^2
High Importance	2.2633	0.9691
Medium-to-High Importance	1.3926	0.9883
All Features	1.3285	0.9894

The results indicate that each feature influences the model's predictive power regardless of its importance score.

Comparison of Algorithms

The performance of four machine learning models - Random Forest, CatBoost, XGBoost, and a Stacked Model combining all three - was evaluated using the All Features set. The performance metrics, RMSE and R^2, for each model are summarised in Table 6.

Table 6. Performance Metrics Across Different Algorithms Using the All Features Set

Algorithm	RMSE (kWh)	R^2
Random Forest	1.3285	0.9894
CatBoost	1.3755	0.9886
XGBoost	1.4358	0.9876
Stacked Model (RF, CatBoost, XGB)	1.2842	0.9901

As observed, the Stacked Model yields the lowest RMSE and highest R^2, emerging as the most effective algorithm for this particular task. Random Forest, CatBoost, and XGBoost also exhibit strong performances but are slightly less effective in terms of both RMSE and R^2. These results reinforce the efficacy of ensemble algorithms in capturing the complexities of electricity consumption patterns. The slight variations in performance metrics among the algorithms indicate that the Stacked Model offers the best performance.

Practical Implications and Model Validation

In this section, we validate our best-performing model, the Stacked Model, on unseen data for April 2022 and discuss the practical implications of its predictions. These real-world validations underscore model utility as a diagnostic tool for facility management.

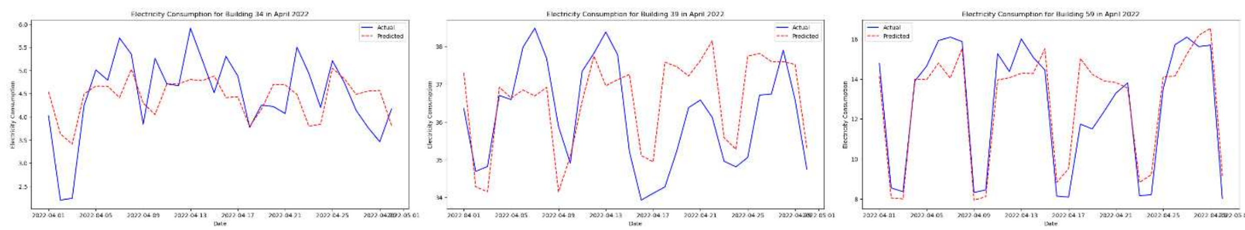

Figure. 2. Electricity Consumption Comparison for Buildings 34, 39, and 59

Building 34, 39, and 59 For these buildings, Our model showed a high level of accuracy, consistent with the findings of Liu et al. (2019), with a difference of only 1.67, 12.36, and 2.88 kWh/month between the actual and predicted consumption. It implies the building is already operating optimally, especially regarding HVAC system efficiency. Thus, the facility managers could continue with the current energy management practices.

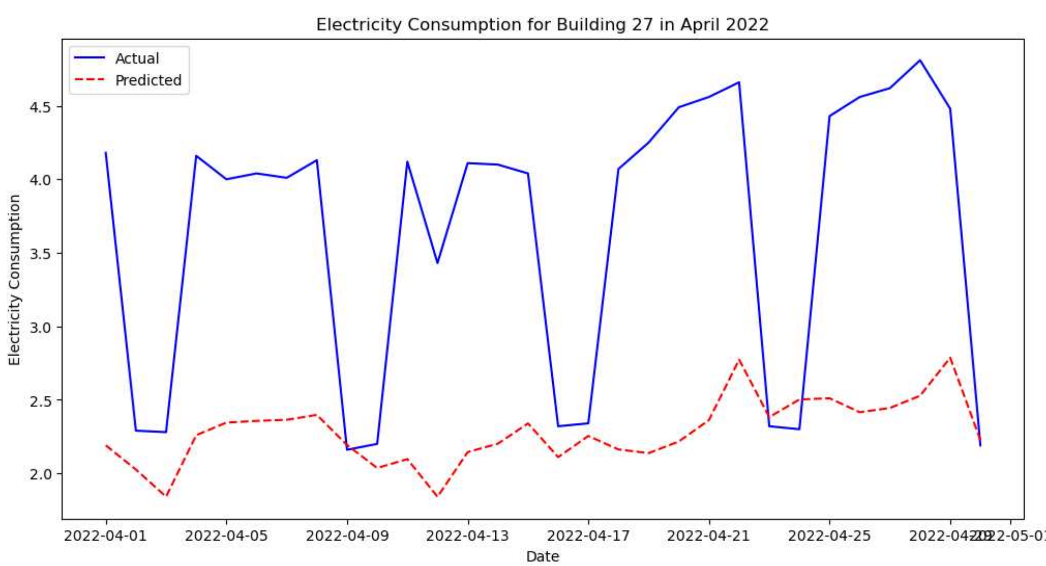

Figure. 3. Electricity Consumption Comparison for Building 27

Building 27 The model significantly underpredicted the consumption by around 41.21 kWh/month. This underprediction translates to a potential cost-saving opportunity, similar to the energy optimisation strategies discussed by Aram et al. (2022). If the HVAC system were to be tuned to meet the model's predictions, this campus could save approximately 18.66 AUD that month, assuming an electricity rate of 45 cents (AUD) per kWh (Australia Electricity Prices, 2022). Therefore, these results signal facility managers to investigate potential avenues for energy optimisation, particularly concerning the HVAC system.

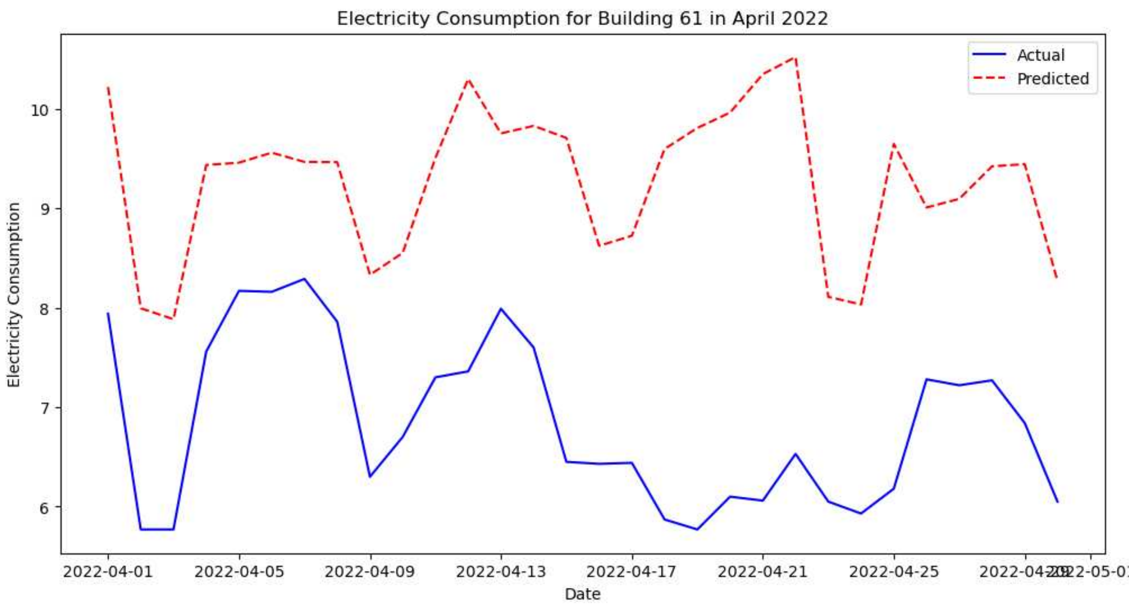

Figure. 4. Electricity Consumption Comparison for Building 61

Building 61 The model overpredicted the actual consumption by approximately 72.84 kWh/month. It indicates that the building might have implemented additional energy-saving measures, such as LED installations, that were not captured in the model. Therefore, the facility managers are likely already employing effective strategies for energy conservation.

CONCLUSION

We have comprehensively evaluated the performance of multiple machine learning algorithms in predicting building electricity consumption. Building 61 has a discrepancy that deserves commendation rather than concern. Unlike Buildings 34, 39, and 59, which aim to align actual consumption with predictions, Building 61 serves as an example of the ideal scenario: not just meeting but exceeding expectations by consuming less than predicted. It indicates effective energy management practices, contributes to broader sustainability initiatives that align with the goals outlined (Aram et al., 2022) and helps the campus move closer to achieving Net Zero Carbon Emissions by 2029. It causes the exceeding energy efficiency predictions, as in the case of Building 61, to be viewed as a positive step toward a more prominent environmental goal.

By analysing the discrepancies between predicted and actual consumption, facility managers can gain valuable insights into building performance, thereby allowing for more targeted energy-saving interventions. We present the quantitative results of our algorithms' comparisons and the practical implications of using such a model for real-world applications.

The outcomes of this study open various avenues for future research and practical applications. The current model focuses on specific buildings, mainly within the academic domain. A natural extension would incorporate data from numerous residential, commercial, and industrial building types. This expansion tests the model's versatility and broadens its applicability. Building upon the expanded dataset, the predictive model can be the backbone for an automated energy efficiency recommendation system. This system could provide actionable insights tailored to each building type, suggesting specific energy-saving measures, notably concerning HVAC systems and lighting.

ACKNOWLEDGMENT

We are thankful to La Trobe University for providing the open dataset named "UNICON Energy Consumption Dataset" on Kaggle, an essential resource for this research. We have utilised this dataset solely for academic purposes, not commercial gain.

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Evaluating the Impact of Different Feature Scaling Techniques on Breast Cancer Prediction Accuracy

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ABSTRACT

Objective: To investigate the influence of different feature scaling techniques on the performance of machine learning algorithms in breast cancer prediction and identify the optimal combination of algorithm and scaler that yields the highest predictive accuracy.

Method: Machine Learning Models (SVM, AdaBoost and RF), Feature Scaling Techniques (StandardScaler, MinMaxScaler, RobustScaler and Normalizer)

Result: Effect of Feature Scaling. For SVM, feature scaling improved the performance. The best accuracy (98.25%) was obtained with MinMaxScaler. AdaBoost's performance remained consistent (~97.66%) across all scaling techniques. RF showed minor variations in performance across different scalers, but the differences were marginal.

Conclusion: By experimenting with different combinations, practitioners can optimise model performance, ensuring more reliable and accurate predictions.

Recommendation & Implication: Considering more than 30 features using a larger dataset in further study. Fine-tuning might lead to different results, testing the model with real-world data and exploring other preprocessing methods.

Keywords: *Machine Learning (ML), Breast Cancer Prediction Accuracy, Feature Scaling*

INTRODUCTION

Breast cancer is one of the most common cancers in women worldwide. Studying the frequency and factors that cause this disease is essential in developing methods of prevention and caution. Thus, Breast cancer is a subject of research interest due to its devastating impact on women's health and the increasing damage to society and health systems caused by the disease. Here are some reasons why research is ongoing on breast cancer.

Severity of Breast Cancer: Breast cancer is very severe and damaging to the patient. Research to develop effective methods for detecting and treating breast cancer is vital to reduce the severity of this disease and increase the chance of successful treatment. The complexity of breast cancer: There are many distinct types of breast cancer and differences in how cancer cells behave. This study creates a need to study and understand the genetics and behaviour of this disease.

This study conducts training and testing using the UCI open database (Bache & Lichman, 2013), which holds both benign and malignant tumour types. Malignant tumours are cancerous, while benign tumours are non-cancerous. Many researchers are still working on finding ways to detect and diagnose cancer early. Because early-stage cancer is less expensive and easier to treat, many researchers are still working on developing a proper diagnosis method. As a result, treatment can begin sooner, and the resolution rate may increase. The primary aim of this study is to evaluate several machine learning (ML) algorithms and identify the most efficient method for breast cancer detection. The prediction of breast cancer can be applied in various ways using machine learning. (Naji et al., 2021) employed five machine learning methods—namely Support Vector Machine (SVM), Random Forest, Logistic Regression, Decision Tree, and K-Nearest Neighbours (KNN)— found that SVM achieved the highest accuracy at 97.2%. (Uddin et al., 2023) expanded the scope to include additional algorithms such as Naïve Bayes, AdaBoost, Gradient Boosting, Multi-layer Perceptron, and Nearest Cluster Classifier. Utilising multiple performance metrics, including error rate, accuracy, precision, F1-score, and recall, they determined that the Voting Classifier outperformed others with an accuracy rate of 98.77% and the lowest error rate. Similarly, (Algherairy et al., 2022) found that a Logistic Regression model using Forward Selection achieved exceptional performance, with a classification accuracy of 98.2%, a precision score of 98.3%, and an F1-score of 98.6%.

LITERATURE REVIEW

This segment explores scholarly works related to Ensemble Learning to enhance the model's predictive accuracy, classification capabilities, and overall performance metrics.

This research (Algherairy et al., 2022) is to scrutinise the categorization and identification of breast cancer using the Wisconsin Breast Cancer Diagnostic (WBCD) dataset. Various feature selection methods, such as Pearson's Correlation, Forward Selection, Mutual Information, and Univariate ROC-AUC, were employed to assess the importance of different attributes. Multiple machine learning algorithms, including Support Vector Machine (SVM), Logistic Regression, and XGBoost, were implemented, and their performance was gauged using metrics like accuracy, precision, recall, and F1-score. Among the tested algorithms, Logistic Regression using Forward Selection appeared as the most effective classifier, recording high accuracy, precision, and F1-score scores. Meanwhile, the SVM model employing Pearson's Correlation for feature selection yielded the maximum recall score. The constructed model offers promising capabilities for aiding healthcare professionals in early breast cancer diagnosis.

Naji et al. (2021) evaluated the effectiveness of five distinct machine learning techniques — specifically Support Vector Machine (SVM), Random Forest, Logistic Regression, C4.5 Decision Tree, and K-Nearest Neighbours (KNN) — in the context of breast cancer prediction. To do so, they initially obtained and preprocessed the data from the Wisconsin Diagnostic dataset for breast cancer. This preprocessing phase involved data cleaning, attribute selection, target role assignment, and feature extraction. To evaluate the performance of each algorithm, the researchers divided the tagged information into different sets for training and testing, distributing 75% of the information for model training and 25% for testing purposes. The models' accuracy was then compared to determine the most reliable algorithm for detecting breast cancer.

Hamid et al. (2021) introduces an ensemble filter feature selection technique that employs Particle Swarm Optimization (PSO) in conjunction with Support Vector Machine (SVM) to refine the identification of relevant features and optimise kernel parameters within medical data analytics. This approach considers the interconnectedness among features and looks to enhance the precision of the classification mechanism. Experimental evaluations conducted on Breast Cancer and Lymphography datasets show that the proposed method surpasses existing approaches in achieving superior classifier accuracy and delivering optimally significant features. Heaton (2016) exhibits that diverse machine learning models show dissimilarities concerning different engineered features, thereby emphasising the significance of selecting the most proper elements for achieving the best model performance.

The Support Vector Machine (SVM) is a supervised learning approach often used for regression and classification exercises. It is widely recognized in machine learning for its ability to categorise data effectively. SVM aims to find the optimal line or boundary that can accurately classify data points into diverse groups, thereby enabling subsequent data points into the proper category (Gothai et al., 2023). Support Vector Machine (SVM) is a technique for machine learning that is utilised for the tasks of classification and regression. This algorithm is considered cutting-edge and has been extensively used in predicting clinical drug response for cancer patients. SVM is among the machine learning algorithms utilised in the investigation to contrast the proposed transfer learning approaches with the baseline approaches. The investigation also highlights the utilisation of SVM in the context of breast cancer and multiple myeloma patients, wherein the proposed transfer learning approaches exhibited superior performance compared to the baseline algorithms (Turki & Wang, 2019).

Random Forest is a technique utilised in data mining to carry out classification and regression tasks. It can be described as an ensemble learning method combining multiple decision trees to generate predictions. Each decision tree within the random forest is trained using a random subset of the available training data and employing a random subset of the input features. The final prediction is obtained by aggregating the predictions made by each decision tree. Random Forest is renowned for its proficiency in handling high-dimensional data and effectively managing missing values. Furthermore, it demonstrates resistance to overfitting and has proven accurate in predicting heart diseases. In the specific domain of heart disease prediction, Random Forest has undergone evaluation and has been determined to achieve a high level of accuracy (Ouf & ElSeddawy, 2021).

Uddin et al. (2023) examines using a range of machine learning algorithms in diagnosing breast cancer, utilising the Wisconsin Breast Cancer Dataset for training. The inquiry incorporated a diverse set of classifiers, encompassing the Support Vector Machine, Random Forest, K-Nearest Neighbors, Decision Tree, Naïve Bayes, Logistic Regression, AdaBoost, Gradient Boosting, Multi-layer Perceptron, Nearest Cluster Classifier, and a Voting Classifier. Among these, the Voting Classifier exhibited superior performance, reaching an accuracy rate of 98.77% and the smallest error margin. In addition, without optimization, the Voting Classifier still manifested a high accuracy rate of 96.50%, which subsequently improved to 98.77% following optimization. Consequently, the Voting Classifier emerges as the most efficacious model for prognosticating breast cancer within this investigation.

The procedure of feature engineering refers to converting unprocessed data into a structure compatible with machine learning algorithms. This process encompasses the creation of novel attributes or adjustments to pre-existing ones to enhance the efficacy of a given model. Conventionally, feature engineering has been an effortless task requiring manual effort and a deep understanding of the subject matter (Chen et al., 2019).

Feature importance is a prevalent explanation technique in explainable artificial intelligence, helping users understand machine learning model behaviour. Various methods, including global and local approaches, gauge feature importance. The significance of expressive features varies by technique, and combining multiple explanation techniques can yield more reliable results. Local explanations are particularly valuable in critical cases, such as false negatives. Logistic regression with L1 penalization and random forest are standard techniques for measuring feature importance. Logistic regression calculates feature coefficients using all features as input, while random forest computes importance values for each feature individually. Random forests provide feature importance measures through Gini importance, which decreases when the probabilities of classes 1 and 2 are equal (Saarela & Jauhiainen, 2021).

The methods used in feature selection techniques and feature importance often show similarities. Most of the time, feature selection is used before or during model training. This application aims to choose the critical characteristics of the finished input data. In contrast, feature significance metrics are used during or after training to explain the model's learned information (Saarela & Jauhiainen, 2021). The article comprehensively reviews machine learning models used to predict survival time in lung cancer patients. The study evaluates the accuracy of various machine learning algorithms for different time intervals. The results show that processed features with the MaxMinScaler technique with different algorithms perform better for different time intervals, with Random Forest, Logistic Regression, and Support Vector Machines being among the most accurate models. The study also discusses the limitations of the reviewed models and provides recommendations for future research (Altuhaifa, Win & Su, 2023).

This article discusses the use of machine learning and deep learning techniques for classifying breast cancer histopathological images as benign or malignant. The authors compare the performance of different pre-trained convolutional neural network (CNN) models, including ResNet-50, VGG-19, AlexNet, and Inception-v3, and employ random forest and k-nearest neighbours algorithms for classification. The experiments are conducted using the BreakHis public dataset, and the results show that the ResNet-50 network achieves the highest test accuracy of 97% for breast cancer classification (Leow et al., 2023).

The study further compares the performance of various established models for breast cancer classification with the proposed model. The proposed model, which combines feature selection, feature extraction, and machine learning techniques with DT, RF, KNN, NB and SVC, which feature scaling using the StandardScaler technique, outperforms all other models in terms of accuracy, precision, recall, and F1-score. Consequently, the study concludes that the proposed model is the most effective approach for breast cancer classification (Kapila & Saleti, 2023).

RESEARCH METHODOLOGY

In this section, we aim to prepare the dataset for prediction. The Breast Cancer Wisconsin (Diagnostic) Dataset allows the application of Machine learning techniques in such a research process. A key step before deploying any Machine Learning algorithm is to study the characteristics of the given dataset. The dataset collected from features is computed from a digitised image of a breast mass's fine needle aspirate (FNA). They describe the characteristics of the cell nuclei present in the image.

A: process; in this paper, the researchers would like to efficiently deliver predictive analytics solutions and intelligent applications. CRISP-DM, which stands for Cross-Industry Standard Process for Data Mining, is a widely used framework for guiding data mining and machine learning projects as shown in Figure 1. It supplies a structured approach to data mining, from understanding the problem to deploying the model in a production environment. CRISP-DM is a comprehensive and iterative method that helps data scientists and analysts navigate the complexities of data mining projects (Chapman et al., 2000).

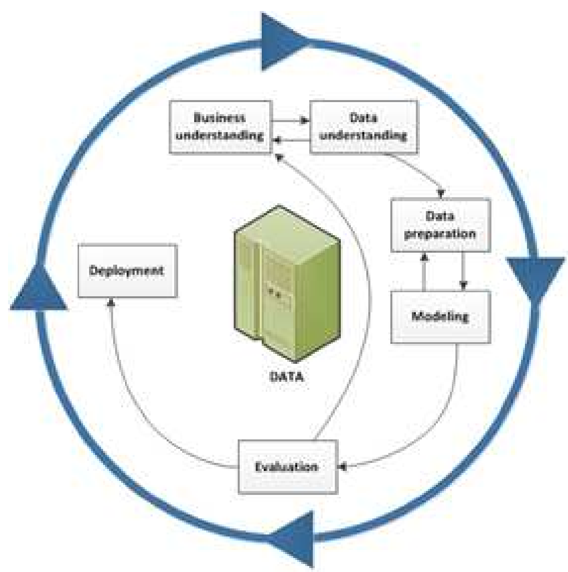
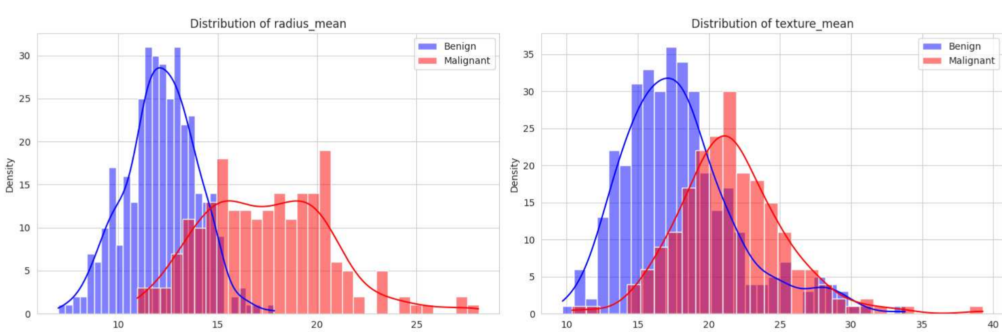


Fig. 1 CRISP-DM process (Chapman et al., 2000)

B: Breast cancer is a disease in which abnormal breast cells grow out of control and form tumours. If left unchecked, the tumours can spread throughout the body and become fatal. Breast cancer cells begin inside the milk ducts and/or the milk-producing lobules of the breast. The earliest form (in situ) is not life-threatening. Cancer cells can spread into nearby breast tissue, creating tumours that cause lumps or thickening. Invasive cancers can spread to nearby lymph nodes or other organs (metastasize). Metastasis can be fatal. Treatment is based on the person, the type of cancer and its spread, and it combines surgery, radiation therapy and medications.

C: Data Understanding, Wisconsin Diagnostic Breast Cancer (WDBC), The data contain measurements on cells in suspicious lumps in a woman's breast. Features are computed from a digitised image of a breast mass's fine needle aspirate (FNA). They describe the characteristics of the cell nuclei present in the image. All samples are classified as either benign or malignant. Data Format: WDBC is a dataset with 31 columns. The first column shows whether the sample is classified as benign (B) or malignant (M). The remaining columns contain measurements for 30 features. Details: Ten real-valued features are computed for each cell nucleus: radius (mean of distances from centre to points on the perimeter), texture (standard deviation of grey-scale values), perimeter, area, smoothness (local variation in radius lengths), compactness (perimeter ^{2} / area - 1.0), concavity (severity of concave portions of the contour), concave points (number of concave portions of the contour), symmetry and fractal dimension ("coastline approximation" - 1). The references listed below contain detailed descriptions of how these features are computed. The mean, standard error, and "worst" or largest (mean of the three largest values) of these features were computed for each image, resulting in 30 features.

D. Data Preparation: This phase involves data cleaning, transformation, and preprocessing to ensure the data is ready for analysis. Data preparation is crucial, as the data quality greatly impacts the project's success. In this dataset, We observed that the dataset was devoid of missing values, with no need for imputation techniques often required for data cleansing. The diagnosis column has been successfully converted to numerical format, with malignant labelled as one and benign as 0. There are 569 entries in the dataset. The diagnosis column (target variable) has a mean value of approximately 0.3726, indicating that around 37.26% of the samples are malignant. The features (e.g., radius_mean, texture_mean, etc.) have different ranges and standard deviations. It is suggested that practitioners consider normalising the features if they use algorithms sensitive to feature scale, which is the distribution of the selected features for benign and malignant diagnoses. radius_mean: Malignant tumours tend to have a larger mean radius than benign tumours. texture_mean: Malignant tumours also tend to have a higher mean texture, although there's some overlap with benign tumours. smoothness_mean: Both benign and malignant tumours have a similar distribution for mean smoothness, but malignant tumours show a slightly wider range. compactness_mean: Malignant tumours generally have higher compactness values compared to benign tumours. These visualisations can provide insights into which features might be more informative for distinguishing between benign and malignant tumours as shown in Figure 2.



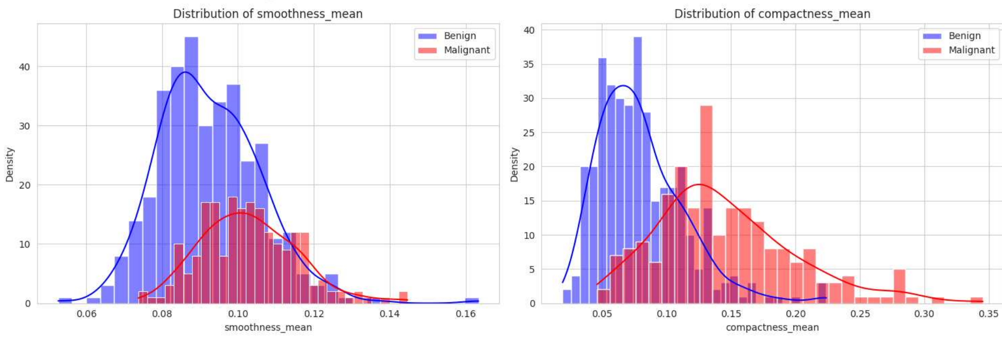


Figure 2. Distribution of Features
(radius_mean, texture_mean, smoothness_mean, and compactness_mean).

Features like concave points_worst, perimeter_worst, concave points_mean, radius_worst, and perimeter_mean strongly correlate with the diagnosis. It means that as these feature values increase, the likelihood of the tumours being malignant also increases. On the other hand, features like smoothness_se and fractal_dimension_mean have a slight negative correlation, indicating that as these feature values increase, the likelihood of the tumour being benign increases. Such insights can be valuable when selecting features for a predictive model or understanding the factors contributing most to malignant diagnoses as shown in Figure 3.

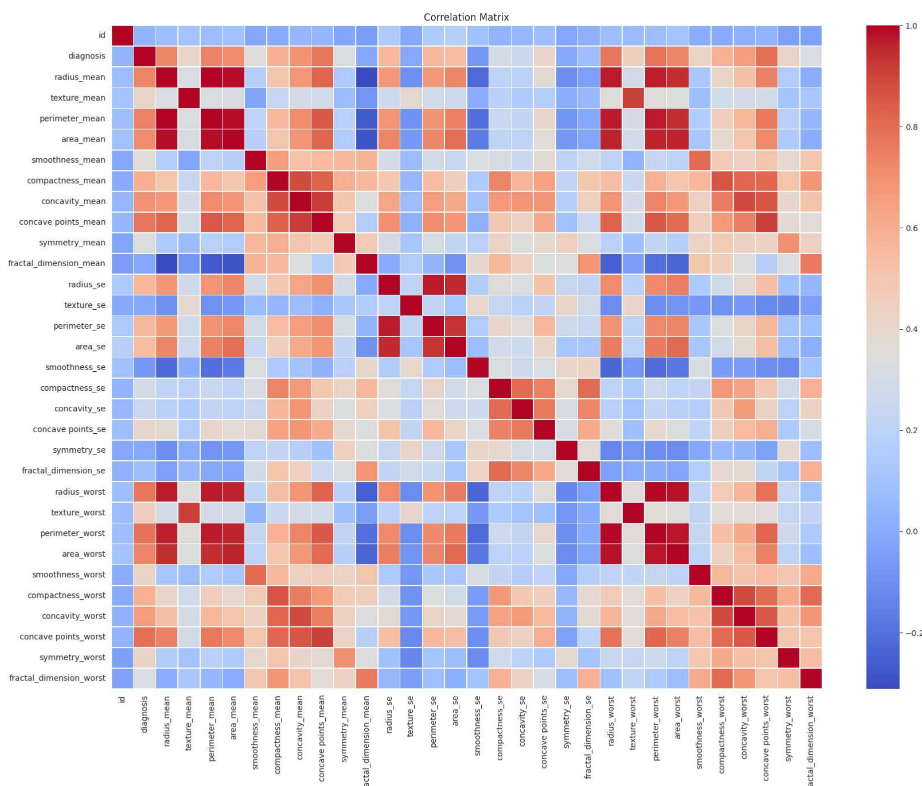


Figure 3. Correlation Matrix with diagnosis.

The dataset is divided into two sets (30 features each): a training dataset, which constitutes 70% of the data, and a testing dataset, which makes up the remaining 30%. The training dataset is used for optimising and training the machine learning models, while the testing dataset is employed to evaluate the classification results generated by all machine learning models.

E: Modelling: in this stage, various modelling techniques are applied to the prepared data to build predictive or descriptive models. Machine learning algorithms are trained and evaluated in this stage to achieve the project objectives. The study used the machine learning model ADB, RF, and SVM for prediction. The accuracy of each model (AdaBoost, SVM, RF) was found when trained on data preprocessed with different scalers (StandardScaler, MinMaxScaler, RobustScaler, Normalizer) as shown in Table 1. AdaBoost's performance remained consistent across all scaling techniques; SVM benefitted the most from 'MinMaxScaler', with a slight increase in accuracy. Random Forest's performance was consistent with most scaling techniques but saw an improvement with 'Normalizer'.

Table 1. Accuracy between Different ML Models with Feature Scaling Techniques

Models	StandardScaler	MinMaxScaler	RobustScaler	Normalizer
AdaBoost	97.66%	97.66%	97.66%	97.66%
SVM	97.66%	98.25%	97.66%	91.81%
RF	97.08%	97.08%	97.08%	97.66%

F: Evaluation of the models (AdaBoost, SVM, and RF) is conducted on data preprocessed with different scalers (StandardScaler, MinMaxScaler, RobustScaler, Normalizer). Performance metrics, including accuracy, precision for Malignant class, recall for Malignant class, F1-Score for Malignant class, Confusion Matrix, are employed for a comprehensive assessment. An analysis of each model's performance across various preprocessing techniques was conducted (Table 2). This stage is instrumental in identifying the optimal combination for a specific dataset.

Table 2. Performance Evaluation between Different ML Models with Feature Scaling Techniques

Models	Scaler	Accuracy	Precision (Malignant)	Recall (Malignant)	F1-Score (Malignant)
AdaBoost	StandardScaler	97.66%	96.83%	96.83%	96.83%
AdaBoost	MinMaxScaler	97.66%	96.83%	96.83%	96.83%
AdaBoost	RobustScaler	97.66%	96.83%	96.83%	96.83%
AdaBoost	Normalizer	97.66%	94.03%	100.00%	96.92%
SVM	StandardScaler	97.66%	96.83%	96.83%	96.83%
SVM	MinMaxScaler	98.25%	98.39%	96.83%	97.60%
SVM	RobustScaler	97.66%	96.83%	96.83%	96.83%
SVM	Normalizer	91.81%	100.00%	77.78%	87.50%
RF	StandardScaler	97.08%	98.33%	93.65%	95.94%
RF	MinMaxScaler	97.08%	98.33%	93.65%	95.94%
RF	RobustScaler	97.08%	98.33%	93.65%	95.94%
RF	Normalizer	97.66%	96.83%	96.83%	96.83%

RESULTS

We obtained from our analysis, Data Overview: The dataset consisted of features related to breast cancer tumours, with labels showing whether tumours were benign or malignant. There were 30 features and one target variable in the dataset. Modelling Without Scaling, SVM achieved an accuracy of 63.74% without feature scaling. AdaBoost achieved an accuracy of 97.66% without feature scaling. RF achieved an accuracy of 97.08% without feature scaling. Effect of Feature Scaling: For SVM, feature scaling improved the performance. The best accuracy (98.25%) was obtained with 'MinMaxScaler'. AdaBoost's performance remained consistent (~97.66%) across all scaling techniques (StandardScaler, MinMaxScaler, RobustScaler, Normalizer). RF showed minor variations in performance across different scalers, but the differences were marginal. Key Insights: SVM is sensitive to feature scaling. Scaling techniques, especially MinMaxScaler, significantly improved its performance. AdaBoost displayed robustness to feature scaling, with consistent performance across different preprocessing techniques. RF, being a tree-based algorithm, was less sensitive to the scale of the data, showing consistent results across different scaling methods. Recommendation: if computational resources allow, it's a good practice to experiment with different preprocessing techniques and models to find the best combination for a given dataset. For this dataset, SVM with 'MinMaxScaler' or AdaBoost with any scaler seems to be the best choice, achieving accuracies close to or above 98%.

CONCLUSION

Our exploration of the breast cancer dataset revealed the significance of feature scaling, especially when working with certain algorithms like SVM. While SVM displayed a pronounced sensitivity to the scale of the data, seeing vast improvements in accuracy with proper scaling, AdaBoost remained remarkably resilient, delivering consistent performance across various preprocessing techniques. Random Forest, a tree-based algorithm, also demonstrated a degree of insensitivity to feature scaling. Among the tested scaling methods, 'MinMaxScaler' stood out for SVM, pushing its accuracy to an impressive 98.25%. AdaBoost consistently achieved an accuracy of around 97.66%, regardless of the scaler used, highlighting its robustness in this context. In the realm of machine learning, there is rarely a one-size-fits-all solution. This analysis underscores the importance of understanding the nuances of each algorithm and the potential impact of data preprocessing. Practitioners can optimise model performance by experimenting with combinations, ensuring more reliable and accurate predictions.

LIMITATION AND RECOMMENDATION

Limitations are that larger datasets might yield different results or nuances in model performance; only 30 features were considered in this dataset. Including more features such as genetic information or more detailed patient histories might improve or alter the model's performance; the models were trained using default hyperparameters. Fine-tuning might lead to different results. The models were trained and tested on a single dataset, and some other preprocessing methods or transformations might influence model performance.

Recommendations are conducted a comprehensive hyperparameter tuning using techniques like grid search or random search to optimise model performance further, Implement k-fold cross-validation to ensure that the model's performance is consistent across different data splits, Explore additional Feature engineering or selection techniques to enhance the predictive power of the models potentially, consider leveraging ensemble methods or stacking multiple models to improve accuracy further, test the models in real-world scenarios or on different datasets to ensure generalizability and explore deep learning techniques which might offer enhanced performance for such classification tasks.

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