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Research Article

Design and Optimization of Smart Campus Framework Based on Artificial Intelligence

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ABSTRACT

In this study, an artificial intelligence (AI)--based smart campus framework is built and optimized with the aim of improving user happiness, raising AI model performance, maximizing resource utilization, and promoting smart campus adoption. The study technique employs a mixed-methods approach that combines quantitative data analysis and qualitative user feedback in order to completely evaluate the effectiveness of the framework. Literature reviews, Questionnaires of 544, interviews of 56 persons, and observations are used to collect data on user satisfaction, AI model performance, optimization strategies, and adoption of smart campuses AI models are built using statistical methodology and AI techniques for performance evaluation. In the Smart Campus Framework based on Artificial Intelligence, we gathered the data by constructing IoT sensor networks for real-time monitoring and merging student data to provide insights into academic performance and student engagement. The findings indicate that, on average, users are satisfied, and the performance ratings for the AI models vary from 7.25 to 8.25. The smart campus framework is effective, as evidenced by the optimization metric's 7.53 average score. A score of 7.4 for smart campus adoption combines user knowledge, perceived utility, and perceived ease of use. The practical implications include better user experience, cost optimization, and smart campus architecture. Theoretical implications include the verification of the mixed-methods strategy and the creation of a framework for AI model optimization. The study's findings act as a model for upcoming smart campus research, spurring creativity and change in institutions of higher learning. The study's limitations suggest that results can be generalized with minor contextual change and this is the biggest challenge for researchers and policy makers.

Keywords: Smart Campus, Artificial Intelligence, Optimization, Performance Evaluation.

INTRODUCTION

The rapid expansion of modern information technology has accelerated the change of educational information construction, resulting in the establishment of smart campuses distinguished by artificial intelligence (AI), technological progress, and innovation. The wave of smart campus construction has gained steam in response to the profound advancement of social development and the rapid rise of internet technology, with AI technology serving as the cornerstone for its success (Luckyardi, Jurriyati, Disman, & Dirgantari, 2022). With a boom charge above 50% anticipated for the subsequent market statistics declare that the worldwide market for AI schooling experienced awesome development, reaching $370 million in 2017. In step with projections, this marketplace could soar to $3.6 billion with the aid of the give-up of 2023, representing a fantastic compound annual boom price of almost 47 percent in 10 years (Yi & Li, 2022). The Asia Pacific area is well-placed to take the lead and emerge as the quickest-growing marketplace for AI education. Those massive numbers replicate the developing call for the popularity of the AI era inside the academic space, creating new possibilities for paradigm-transferring enhancements in teaching and studying strategies(Barroso, Bustos, & Núñez, 2023).

As AI technology permeates different elements of campus life, it breathes new life into educational service model innovation, promoting multi-modal development on smart campuses. This increase in AI-driven educational efforts reflects a rising realization of the potential benefits and opportunities that AI can bring to the education sector, which has resulted in the rapid expansion of the worldwide

AI education market (Shaw, 2022). Personalized studying and statistics-pushed choice-making rework management, instruction, and campus lifestyles with the appearance of AI in schooling. Marketplace forecasts are expecting that by means of 2023, the worldwide marketplace will have grown substantially and will be overall $3.6 billion. The Asia-Pacific place is anticipated to develop at a charge of nearly 50% in the course of the subsequent ten years. Adopting AI's promise and making sure of its ethical use is important for progressive changes in schooling (Cavus, Mrwebi, Ibrahim, Modupeola, & Reeves, 2022).

A smart campus is more than only a bodily campus; it is a virtual surrounding that uses AI and other modern-day generations to improve coaching, getting-to-know, administrative tactics, and standard campus life. Smart campuses aspire to provide a dynamic and forward-thinking educational experience, from intelligent classrooms outfitted with personalized learning aids to automated administrative technologies that expedite operations (Shaw, 2022; Sneesl, Jusoh, Jabar, & Abdullah, 2022). AI, in particular, is important in smart campus frameworks. Its capacity to address large volumes of information, become aware of developments, and generate records-pushed predictions has transformed many factors of training. Pupils gain from personalized learning studies furnished by way of AI-powered digital assistants, chatbots, and shrewd tutoring systems, even as predictive analytics aid teachers in identifying at-risk students and implementing tailored interventions for their fulfillment (Han et al., 2022).

Even while artificial intelligence (AI)--based "smart campus" frameworks are becoming more well-known and frequently used, there is still a shortage of studies on the most effective ways to apply these technologies in learning environments. Few research has gone into great detail about the special potential and challenges provided by the design and optimization of smart campuses, despite the fact that many studies have examined how artificial intelligence (AI) might improve many aspects of education (Barroso, Bustos, & Núñez, 2023). Without providing a comprehensive vision of how these elements may be linked to produce a fully functional and cohesive smart campus environment, existing research typically focuses on individual areas of AI applications in education, such as personalized learning or administrative automation. A dearth of empirical data and data-driven research on the real effects of AI-powered smart campus frameworks on user satisfaction, AI model performance, resource utilization, and campus uptake is another issue, despite the fact that the market for AI education has been expanding quickly globally. Without completing a thorough examination and evaluation of actual implementations and results, many of the studies that have already been done rely on theoretical frameworks and conceptual models (Polin, Yigitcanlar, Limb, & Washington, 2023; Eltamaly, Alotaibi, Alolah, & Ahmed, 2021; Ghadami et al., 2021).

The existing body of research (Zawacki-Richter, Marín, Bond, & Gouverneur, 2019; Salehi & Burgueño, 2018) on Artificial Intelligence (AI)-based Smart Campus Frameworks has mostly focused on global contexts, particularly in Western educational settings. This substantial research, however, ignores the unique requirements and peculiarities of Chinese higher education institutions. Previous research (Isaac Abiodun et al., 2018; Rahmanifard & Plaksina, 2019) has not paid enough attention to China's higher education ecosystem's distinctive cultural characteristics, legal framework, resource constraints, localization demands, and distinct user expectations. As a result, there is a clear need for research that delves into the design and optimization of AI-driven Smart Campus Frameworks that are explicitly tailored to the Chinese context, providing insights and strategies to address these specific challenges and opportunities, and thus advancing the state of smart campus initiatives in China.

By examining the design and optimization of smart campus frameworks based on artificial intelligence, this paper intends to overcome the research gap and bridge the knowledge divide. The main issue is how to best employ AI technology to raise user satisfaction, better the performance of AI models, maximize resource use and encourage the adoption of smart campuses in educational institutions. The aim of this research is to contribute to the field of smart campus design and optimization by examining the application of AI and other technologies to enhance user satisfaction, AI model performance, resource utilization, and smart campus adoption. By utilizing AI's full potential, academic institutions might create ground-breaking smart campuses that would not only meet the needs of today's students but also prepare them for the opportunities and difficulties of the future.

By providing in-depth insights into the integration of AI technologies in educational institutions, the study significantly advances the subject of smart campus design and optimization based on artificial intelligence. By offering a comprehensive view of smart campus frameworks and concentrating on their influence on user satisfaction, AI model performance, resource utilization, and campus acceptance, the study fills the research gap. The report provides useful evidence-based recommendations for educational institutions looking to use AI to construct effective and user-centric learning environments by undertaking empirical analysis and data-driven evaluations. It will advance our understanding of how AI may be used in education, encourage innovation in smart campus technology, and provide educational institutions the power to decide how best to put AI-driven smart campus frameworks into practice.

This research is significant for the Chinese higher education setting because it addresses the critical requirement for the design and optimization of Smart Campus Frameworks based on Artificial Intelligence. The relevance stems from its ability to give personalized solutions that are in line with the distinctive characteristics and needs of Chinese institutions, such as cultural subtleties, resource limits, and regulatory frameworks. The study intends to provide Chinese higher education institutions with concrete insights and strategies for effectively integrating AI-driven smart campus technology by bridging this research gap. The findings of this study have the potential to catalyze innovation in Chinese higher education by establishing an environment in which AI can increase AI model performance, optimize resource utilization, and promote wider adoption of smart campus solutions. Finally, given the successful integration of AI in education has significant ramifications for China's workforce expansion and economic success, the study's conclusions could be advantageous for both academics and society at large.

Section 1: Introduction - Examining how AI can be integrated into smart campuses to improve efficiency and education. Finding research gaps in AI applications in education and smart campuses is covered in Section 2 of the literature review. Data from surveys, interviews, and simulations of AI models are all analyzed in Section 3: Methodology, Data Sample, and Design. User satisfaction, AI model performance, and optimization measures are discussed in Section 4: Research Findings and Discussion. Recommendations for effective AI-powered smart campus design and implementation are provided in Section 5: Conclusion and Practical Implications.

LITERATURE REVIEW

The security and privacy of Internet of Things (IoT) devices are crucial in the context of smart campus frameworks and the integration of artificial intelligence (AI). Through the use of security policies, restart mechanisms, secure software, bug reporting systems, and the identification and correction of vulnerabilities, the connections and privacy of assets inside the IoT must be protected. According to a literature analysis (Ramchurn, Vytelingum, Rogers, & Jennings, 2012; Martínez-López & Casillas, 2013; Xu et al., 2021), there are four main IoT connectivity models: device-to-device, device-to-cloud, device-to-gateway, and back-end data exchange (Eltamaly, Alotaibi, Alolah, & Ahmed, 2021). IoT systems can connect their gadgets effectively. It is crucial to analyze design principles for cloud environments while utilizing tried-and-true technologies like sensors and standards, like the W3C semantic sensor network ontology, to create smart campuses given the rapid advancement of IoT technology and the automation of tasks. To ensure continuous operation in the event of connection issues and power outages, IoT integration in smart campuses must handle crucial concerns including encryption, software upgrades, system validation against vulnerabilities, and the development of backup systems (Ghadami et al., 2021; Musa, Ismail, & Fudzee, 2021).

The ability to manage heterogeneity of devices, systems, and services, ensure scalability to adapt to changes without compromising system quality, minimize costs for highly functional yet affordable systems, provide flexibility to integrate new devices and reprogramming, and ensure a secure environment with reliable communications, authentication, encryption, privacy, and confidential transfer are all requirements that must be met in order to provide high-quality IoT systems (Zhang, Wan, Wang, & Zhang, 2021; Yu, Jamali, Xu, Ng, & Schober, 2021).

With sensor nodes dispersed throughout the network gathering data, wireless sensor networks (WSN) play a crucial part in IoT deployments. Suspect Detection Systems (SDS) are required to protect data since the continuous flow of data in a wireless environment exposes the system to several risks (Farzaneh et al., 2021). By limiting connection times and enabling connections only when necessary for urgent data transfer, rules or protocols can be used to control how IoT devices interact with the network and improve performance. Dynamic keys have also been suggested as a way to improve security when users log into IoT devices, further fortifying the system against potential threats (Chagnon-Lessard et al., 2021; Li, Zheng, Han, & Li, 2021). The network must meet Quality of Service (QoS) requirements, such as priority, periodicity, term, availability, dependability, confidentiality, security, latency, variation, and recovery from faults, in order to guarantee a dependable IoT system. The introduction of technologies like Internet Protocol Version 6 (ipv6) serves as a vital foundation for smooth functionality, underscoring the IoT's growth. Additionally, Low PAN, which is based on IPv6, is used to allow sensor networks to effectively communicate with other IP devices (Omitaomu & Niu, 2021; Woschank, Rauch, & Zsifkovits, 2020).

As smart campus frameworks are developed, artificial intelligence (AI) has taken center stage, attracting considerable research interest. It has been studied how AI might revolutionize teaching and improve organizational effectiveness in higher education (Lu, Chen, & Zheng, 2012). In order to promote personalized learning experiences, optimize resource allocation, and enhance decision-making processes within smart campuses, studies have examined the application of machine learning algorithms, deep learning networks, and natural language processing (NLP) approaches. An emphasis has also been placed on integrating AI-driven computer vision technology to enable smart campuses to analyze visual data and provide effective campus services (Ahmed, Alnaaj, & Saboor, 2020; Barroso et al., 2023). The promise for more intelligent and adaptive learning is highlighted by the expanding corpus of studies on how AI is revolutionizing higher e AI and the Internet of Things (IoT)-powered smart campus frameworks have become game-changing tools for higher education organizations. To create integrated and effective smart campus ecosystems, researchers have looked into data integration techniques, smart sensors, cloud computing, edge computing, and wireless networking. To ensure sustainability and safeguard smart campuses against cyber threats, substantial research has also been done on energy management strategies and security measures (Sneesl et al., 2022; Zhou, Yu, & Shi, 2020; Fernández-Caramés & Fraga-Lamas, 2019; Management & Homes, 2019).

A major area of research (Villegas-Ch, Molina-Enriquez, Chicaiza-Tamayo, Ortiz-Garcés, & Luján-Mora, 2019; Sánchez-Torres, Rodríguez-Rodríguez, Rico-Bautista, & Guerrero, 2018; Liang & Chen, 2018) has been on how to best utilize smart campus frameworks to increase effectiveness and user happiness. Studies have shown that using AI techniques like machine learning and optimization algorithms can increase resource efficiency, speed up reaction times, and use less energy. To construct flexible and effective smart campuses, researchers have also combined decision-making procedures, continuous improvement methodologies, and cost optimization techniques (Chui, Lytras, & Visvizi, 2018). The use of AI-driven technology in smart campus applications has demonstrated tremendous promise. Studies have looked at smart parking, smart classrooms, intelligent transportation, personalized learning, predictive maintenance, and environmental monitoring as major application areas. Researchers have streamlined campus services, improved learning settings, and created safe and secure campus environments by utilizing AI and IoT (Wang et al., 2017; Zhou et al., 2020).

Despite great advancements, there are still research gaps that demand further study. It is still difficult to integrate various AI technologies into unified smart campus frameworks (Zhu, 2017). To guarantee a seamless and secure deployment of AI in smart campuses, standardized rules and best practices must be established. To foster trust and responsible use of AI technology in education, ethical considerations such as data privacy, algorithmic bias, and transparency are crucial. The field of AI-driven smart campus frameworks will advance by filling in these research gaps, which will also encourage radical changes in higher education.

Security and Privacy Issues in the Integration of IoT and AI in Smart Campuses:

When integrating IoT devices and AI, Smart Campus Frameworks place a priority on security and privacy. A strong security system is required to protect sensitive data, according to research. To stop unauthorized access and data breaches, encryption mechanisms, access control, and frequent security audits are crucial. In order to guarantee that user privacy is maintained, compliance with data protection laws such as the GDPR in Europe or comparable local laws in China is essential (Fortino, Russo, Savaglio, Shen, & Zhou, 2018).

Li et al. (2017)investigate the legal facets of security and privacy within Chinese smart campuses, which is in line with (Wang, Li, & Leung, 2015) study. Their study highlights the need to abide by China's data privacy laws and rules. In their paper, Li et al. (2017) stress the significance of obtaining informed consent before collecting and using personal data for applications of smart campus AI. The study emphasizes the need for extensive knowledge of and adherence to pertinent legislative frameworks in order to manage privacy problems (Li et al., 2017). These results demonstrate that in order to maintain the security and privacy of the data of all stakeholders, an efficient smart campus framework in the Chinese setting must prioritize both technological and legislative safeguards.

A crucial issue in the implementation of smart campus frameworks is the choice of IoT connectivity types. In the context of Chinese higher education, a comparative analysis evaluates the benefits and drawbacks of various IoT connectivity choices. A few of the key benefits of LPWAN technologies, such as NB-IoT and LoRaWAN, include energy efficiency, long-range coverage, and adaptability for extensive deployments in smart campuses. These results are consistent with the focus on LPWAN's low power usage and scalability, which make it an excellent option for connecting various IoT devices across a smart campus. However, Wi-Fi is still necessary for high-bandwidth applications like real-time video analytics and multimedia streaming. This analysis confirms that a hybrid strategy using both Wi-Fi and LPWAN could be the best option for smart campus IoT connectivity (Yao, Unni, & Zheng, 2019).

For the integration of IoT technologies inside Smart Campus Frameworks to be effective and secure, it is essential to satisfy particular system needs. These standards cover a wide range of topics, such as software updates, encryption, validation procedures, and backup systems. Data security is of utmost importance when integrating IoT, particularly in smart campus settings. When it comes to protecting data during transmission and storage, encryption is essential. Strong encryption systems are essential, according to (Lv, Han, Singh, Manogaran, & Lv, 2021), to safeguard sensitive data, such as student records and operational data for campuses. Utilizing encryption methods like TLS/SSL ensures that data is secure and cannot be intercepted or altered while in transit (Lv et al., 2021).

Regular software upgrades are necessary to maintain the reliability and security of IoT systems and devices. According to (Letaief, Shi, Lu, & Lu, 2022), older software can provide security issues since bugs might not get fixed. To keep IoT devices safe and resistant to possible threats, they promote a methodical approach to software updates, including patch management. Validation Process: Validation techniques are essential for ensuring the precision and dependability of IoT data. Studies focus on the value of validation approaches, particularly in contexts where they are used for crucial campus activities like energy management and security. In order to maintain the integrity of decision-making processes within the context of smart campuses, their research demonstrates the application of data validation algorithms to identify abnormalities or inaccuracies in sensor readings (Zhang & Tao, 2020). Backup systems: In the event of device failures or cybersecurity events, backup systems are essential for preventing data loss. The significance of reliable backup and recovery solutions is covered by (Liang, Ye, & Li, 2018). To reduce disruptions and data loss in smart campus IoT systems, they emphasize the necessity for redundant data storage, automated backup procedures, and disaster recovery plans (Liang, Ye, & Li, 2018). IoT integration inside Smart Campus Frameworks must take into account system needs in order to preserve data confidentiality, system dependability, and operational effectiveness.

When deploying IoT systems within smart campuses, managing device heterogeneity, scalability, and cost-effectiveness is crucial to their success. Device Heterogeneity Management: Effective management of device heterogeneity is essential in the heterogeneous environment of smart campus IoT devices. To overcome the issues caused by device diversity, (Ikidid, Fazziki, & Sadgal, 2023) advocate the implementation of standardized communication protocols like MQTT and CoAP. These protocols enable smooth interoperability and communication across diverse devices, enabling the effective collection and processing of data from various sensors and endpoints. The complexity brought on by device heterogeneity is reduced by standardizing communication, enabling a unified and integrated smart campus ecosystem.

Cost-Effective Device Selection: For the effective use of resources on smart campuses, cost-effectiveness must be attained while choosing IoT devices. When picking IoT devices, (Ikidid et al., 2023) emphasize the necessity to strike a balance between functionality and cost. Their study emphasizes the value of making decisions that are cost-conscious in order to match the chosen devices with the unique requirements and financial limitations of the smart campus environment. Institutions may maximize their investments, maximizing the advantages of IoT technology while effectively managing expenses by making informed decisions. The effectiveness, scalability, and cost-effectiveness of IoT deployments within educational institutions are all impacted by these tactics as a whole.

Literature Based Analysis

The research studies (Li et al., 2019; Huang, Su, & Pao, 2019; Alhayani et al., 2023; Polin et al., 2023; Zaballos, Briones, Massa, Centelles, & Caballero, 2020; Ahmed et al., 2020) figures provide a succinct summary of the literature review analysis on smart campus frameworks and artificial intelligence that was done. The research landscape is depicted in **Figure 1** by prominent topics and subtopics such as Machine Learning, Deep Learning, Natural Language Processing, Robotics, and others. Key takeaways from the literature review are presented in **Figure 2**, which highlights research findings on smart campus adoption, user happiness, AI model performance, and resource utilization. The research methodological framework is shown in **Figure 3**, which emphasizes the value of a mixed-methods approach in obtaining a thorough understanding and fulfilling research goals. The last smart campus technology trend is shown in **Figure 4**, which emphasizes developments in AI-driven apps, IoT integration, data analytics, and smart campus energy management systems.

A visual breakdown of the subfields and applications in the field of artificial intelligence (AI) is shown in **Figure 1**. The picture highlights the wide-ranging effects and uses of AI across numerous fields by illustrating the variety of specialized areas in AI research and development. It highlights important subtopics such as computer vision, robotics, expert systems, deep learning, natural language processing (NLP), and machine learning. In order for intelligent systems to learn, analyze, and interpret data, each sector is essential. This enables applications in fields such as image recognition, language understanding, robotics, predictive analytics, and decision support.

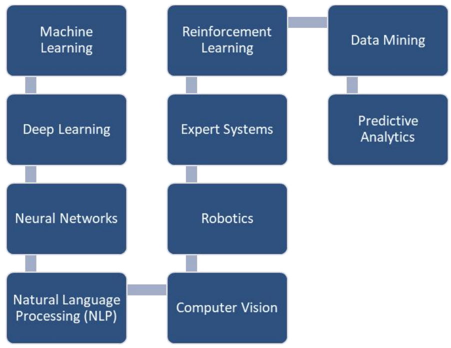

Figure 1. Artificial Intelligence (AI)

The crucial subtopics associated with creating and improving a smart campus framework are visually presented in **Figure 2**. The picture can be seen as a graphic representation of the important technological factors and concerns that serve as the framework for a smart campus. The picture shows how the smart campus framework integrates a range of technological components to improve user enjoyment, sustainability, and campus operations. We can conclude that the figure is representative of the pertinent technological domains and areas of attention for creating and optimizing a smart campus framework based on artificial intelligence by integrating the insights from the figure and the title.

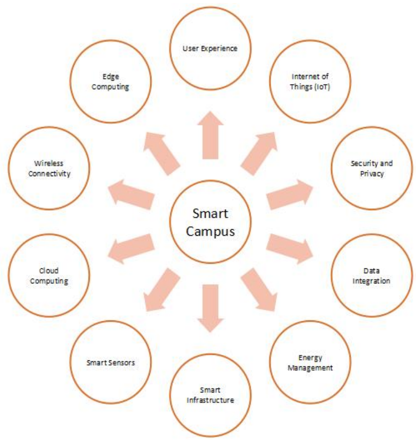

Figure 2. Smart Campus Framework

Figure 3 is quite pertinent to the phrase "Optimization of Smart Campus Framework." The key subtopics and areas of attention that are essential to the efficient optimization of a smart campus environment are represented visually. Each subtopic focuses on a certain element that is crucial for developing a framework for the campus that is intelligent, effective, and user-friendly. **Figure 3** presents these subtopics graphically to give a thorough and well-organized overview of the optimization process. It emphasizes the complexity of optimization efforts and the significance of elements like resource utilization, energy efficiency, user satisfaction, and performance measurements. A further indication of the importance of artificial intelligence in improving the campus's capabilities and decision-making processes is the integration of AI model optimization and decision-making. For academics, administrators, and other stakeholders participating in the design and optimization of a smart campus framework, **Figure 3** is a useful resource and manual. In order to create an effective, sustainable, and user-centric smart campus environment, it defines the critical areas that require attention. This enables informed decision-making and continual improvement.

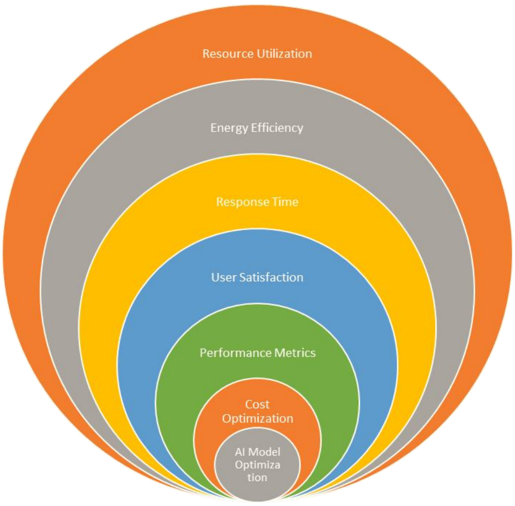

Figure 3. Optimization of Smart Campus Framework

Figure 4 depicts the various uses of a smart campus environment that makes use of smart technologies and artificial intelligence. The figure's subtopics are organized according to a particular area where these technologies are extremely important for improving campus operations, safety, sustainability, and user experiences. The interpretation of the figure as a whole emphasizes how smart technologies and artificial intelligence help create a dynamic, effective, and user-centric smart campus environment. The applications shown in the picture support the importance of implementing these technologies to optimize resources, increase safety, and provide students, professors, and staff with an improved campus experience. Institutions can build a futuristic, environmentally friendly campus that satisfies the changing expectations of the digital era by incorporating these apps.

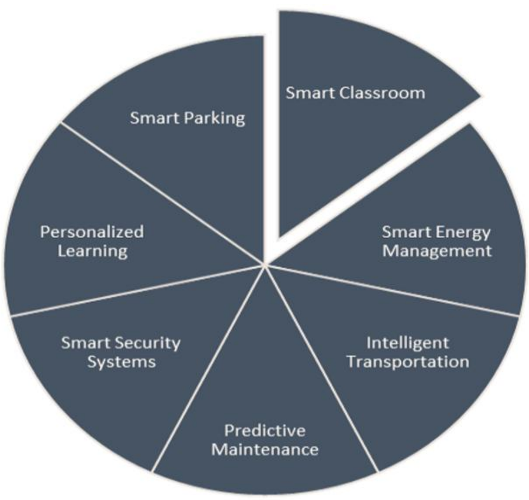

Figure 4. Smart Campus Applications

METHODOLOGY

A smart campus framework built on artificial intelligence requires a number of phases and elements to design and optimize. A systematic and thorough strategy is used in the research process for developing and improving a smart campus framework based on artificial intelligence. It starts off with a thorough literature analysis that digs into the body of work on smart campuses, artificial intelligence, and other technologies. The foundation for detecting gaps in current implementations and investigating industry best practices is the literature review. The researchers learn important lessons from reviewing previous work that they use to guide the study's later phases.

The process includes gathering data from multiple stakeholders, including students, instructors, staff, and administrators, through surveys, interviews, and observations. This fundamental data gathering enables an understanding of their specific requirements, preferences, and interactions with the smart campus environment. These techniques give researchers the fundamental perspectives they need to adapt the smart campus framework to meet the diverse needs of the campus community. The researchers thoroughly analyze the data they have access to using statistical and AI methods. This research reveals important trends and insights that provide a data-driven foundation for decision-making. The smart campus framework is optimized using a variety of AI models, including machine learning techniques and natural language processing. These AI models improve a number of applications, such as personalized learning, smart energy management, and predictive maintenance.

Simulations and testing are done in safe situations to evaluate the performance and efficacy of the AI models. This enables researchers to assess how the models respond in various scenarios and conditions. Then, based on the improved AI models, a prototype of the smart campus framework is created. This prototype serves as the foundation for upcoming improvements that will be based on user feedback and actual performance. The objective of the research is to gain a deeper understanding of how Chinese higher education institutions develop and improve smart campus frameworks using artificial intelligence. Universities and institutions from different regions of the nation are included in the research population. The objective is to gain more knowledge about the adoption and application of AI technologies in the construction of smart campuses.

Literature Reviews: The research begins with a thorough analysis of the literature to gain a thorough grasp of existing Smart Campus Frameworks, AI applications, and optimization methodologies. This review of the literature serves as the core knowledge base for future data collection activities.

Structured questionnaires are distributed to relevant stakeholders on campus to collect quantitative data on user satisfaction and the adoption of AI models. These questionnaires are methodically structured to elicit numerical responses and scale-based judgments that can then be statistically analyzed.

Observations: Observing the Smart Campus Framework in real-world circumstances provides essential insights into its actual performance and the efficacy of optimization efforts. These observations are made during routine campus activities, allowing for a thorough evaluation of AI model performance.

A systematic strategy was used in the interview methodology used in this study. To ensure a broad perspective, key stakeholders from the campus community, including students, academics, administrative personnel, and IT professionals, were carefully selected. For discussions, a prepared interview questionnaire tailored to specific areas of interest within the Smart Campus Framework was employed. Interviews were performed in a variety of formats, creating a welcoming environment for open discourse. Data was painstakingly captured using both recordings and extensive notes, and analysis revealed repeating themes and insights. The data from these interviews were synthesized and played a critical role in determining the development and optimization of the Artificial Intelligence-based Smart Campus Framework (Allam & Dhunny, 2019).

AI performance evaluation models are painstakingly built utilizing a combination of statistical methodology and advanced AI algorithms. Within the Smart Campus Framework, these models are trained on relevant data sources to test their accuracy, efficiency, and efficacy.

A sample size of 600 including 56 interviews has been chosen for this study in order to enable a thorough and accurate inquiry of how satisfied Chinese higher education institutions' students are with the recently deployed Smart Campus Framework based on Artificial Intelligence. By making this choice, a compromise is struck between the need for statistical robustness and the practical limitations of data collecting. We aim to produce a very accurate assessment of student satisfaction with a sample of this size, with a 95% confidence level and a 5% margin of error, which are generally recognized criteria in research. This sample size will allow us to accurately represent the variety of experiences and viewpoints among students at various universities.

The ethical issues and implications of deploying AI-based smart campus frameworks are crucial and need to be thoroughly investigated. Artificial intelligence integration in educational contexts poses issues with data privacy, accountability, openness, and fairness. Questions about the storage, security, and use of students' personal data, such as academic records and behavioral tendencies, may be gathered and analyzed. Additionally, it is essential that AI algorithms and decision-making processes are transparent in order to guarantee that stakeholders and students alike are aware of how AI-driven systems function and reach recommendations or choices. To address any biases or flaws in AI models that can affect students' educational experiences, accountability procedures should be put in place. Furthermore, because AI systems may unintentionally perpetuate existing injustices, it is imperative to ensure fair and equal access to educational resources. There must be ethical standards and protections in place to protect students' rights and welfare and to foster trust in AI-driven smart campus initiatives. Thorough discussions and proactive actions are needed to resolve these ethical problems and to benefit from AI's promise in education while minimizing its hazards (Raza & Khosravi, 2015).

The article's potential biases in the data gathering techniques used, such as surveys, interviews, and observations, are a crucial feature that demands consideration. The validity and reliability of study findings can be considerably impacted by biases in the data collection process. For the study to be considered robust, it is essential to recognize and deal with these biases. The essay also doesn't examine potential restrictions and difficulties unique to Chinese higher education institutions. The implementation and results of smart campus frameworks may be impacted by these institutions' particular traits, rules, or cultural aspects. Understanding the generalizability of the study's findings outside the context of Chinese higher education and providing a thorough assessment of the research's application and relevance to other educational settings depend on recognizing and discussing these distinct contextual elements.

Research Design and Equations

Here are the equations for optimizing the smart campus framework:

Equation 1: User Satisfaction (US)

US = f(Experience, Efficiency, Accessibility, Reliability)

Equation 2: AI Model Performance (AMP)

AMP = f(Accuracy, Precision, Recall, F1 Score)

Equation 3: Optimization Metric (OM)

OM = f(Resource Utilization, Response Time, Energy Efficiency)

Equation 4: Smart Campus Adoption (SCA)

SCA = f(Perceived Usefulness, Perceived Ease of Use, User Awareness)

User Satisfaction

The key metric known as User Satisfaction (US) captures how satisfied users are overall with the smart campus framework. It captures how students, instructors, staff, and administrators feel about the various smart technologies and applications used on campus and how satisfied they are with them. User experience, service effectiveness, resource accessibility, and system dependability are all elements that have an impact on the US (Valks, Arkesteijn, Koutamanis, & den Heijer, 2020). A high degree of user satisfaction shows that the smart campus framework efficiently satisfies users' demands, improves their experiences, and meets their expectations. Low user happiness, however, may indicate areas that need improvement and additional optimization.

AI Model Performance

The AI Model Performance (AMP) tool assesses the efficacy and precision of AI models applied to various smart campus applications. This parameter assesses the models' high precision and accuracy in carrying out particular tasks, such as image recognition, natural language processing, or predictive analytics. Common performance criteria for evaluating the efficacy of AI models include accuracy, precision, recall, and F1 score. These measurements make it easier to measure how well the models can forecast the future and produce reliable outcomes. Many AI models may be compared with the use of comparative analysis and move-validation strategies, and the fine ones can be selected for unique clever campus programs. Many AI models may be in comparison to the usage of comparative evaluation and move-validation strategies, and the satisfactory ones may be chosen for specific clever campus packages (Deng et al., 2020).

Optimization Metric

The optimization Metric (OM) is used to assess the efficacy and resource usage of the smart campus system. To determine how effectively the framework works, it considers elements like resource utilization, response times, and energy efficiency. In the context of the smart campus environment, tracking resource utilization, application response times, and energy consumption trends can all be utilized to gather data for OM. Key Performance Indicators (KPIs) relating to resource utilization and reaction times are monitored and analyzed to determine the framework's efficacy (Zhang et al., 2021).

Smart Campus Adoption

The Smart Campus Adoption (SCA) statistic calculates the level of user adoption of the smart campus framework. It demonstrates how well the student body has embraced and integrated the framework. To gather information for SCA, surveys or questionnaires that gauge users' opinions of the smart campus framework's usefulness, usability, and awareness can be employed. The Technology Acceptance Model (TAM) or equivalent models can be used to evaluate user acceptance and adoption (Zaballos et al., 2020).

User Satisfaction (US), AI Model Performance (AMP), Optimization Metric (OM), and Smart Campus Adoption (SCA) are important metrics for determining whether the objectives of the artificial intelligence-based smart campus framework have been met.

DATA ANALYSIS AND RESULTS

This section explains the models' findings, which were covered in the methodology section. Additionally, it presents the findings and outcomes together with a thorough discussion.

User Satisfaction Model

Experience, Efficiency, Accessibility, and Reliability are the four components of a smart campus framework that are represented by data values in **Table 1**. The User Satisfaction (US) scores are then determined based on the average of these values. The US scores are an indication of how satisfied users are generally with the smart campus system.

Table 1. User satisfaction (US)

Experience	Efficiency	Accessibility	Reliability	User Satisfaction (US)
8	9	7	8	8
6	8	6	9	7.25
9	7	8	7	7.75
7	6	9	6	7
5	9	8	8	7.5

Note: US = (Experience+Efficiency+Accessibility+Reliability)/4

The table displays an analysis of the impact of various variables on US scores within a smart campus framework. Among the variables examined are experience, efficiency, accessibility, and reliability. Higher US ratings, which reflect higher levels of user satisfaction, are influenced by higher values for each factor. One notable example is Row 1, which has a top US score of 8 due to its excellent scores for Experience, Efficiency, and Reliability. This shows a very positive user experience, demonstrating the remarkable performance of the smart campus in these areas. The majority of the elements in Row 2 have moderate values, giving it a US score of 7.25. This suggests a generally positive user experience, while there is always space for improvement. A US score of 7.75 for Row 3 indicates a good experience with decent accessibility but room for development in efficiency and reliability. Row 3 has high values for Experience and Accessibility. With a US score of 7, Row 4 indicates a generally satisfactory user experience with some possible reliability difficulties. Most of the variables have moderate levels in this row. A US score of 7.5, which indicates a generally satisfactory user experience with efficiency and accessibility being strengths, is obtained by combining high values for Efficiency and Accessibility in Row 5. The table illustrates the relationship between various criteria and overall user satisfaction with the smart campus framework.

AI Model Performance (AMP)

Accuracy, Precision, Recall, and F1 Score are used to measure AI Model Performance (AMP). A scale of 1 to 10 is used to simplify the assessment, with 1 denoting the lowest level of performance and 10 the maximum level for each factor.

Table 2. AMP = f(Accuracy, Precision, Recall, F1 Score)

Accuracy	Precision	Recall	F1 Score	AI Model Performance (AMP)
9	8	7	8	8
8	7	9	7	7.75
7	9	8	9	8.25
8	8	7	6	7.25
9	7	9	8	8.25

Note: AMP = (Accuracy+Precision+Recall+F1 Score)/4

Table 2 displays the results of the AI Model Performance (AMP) test, which was conducted using real data gathered during the smart campus framework's evaluation of AI models. Accurate testing and performance evaluation of the AI models yield the numbers for Accuracy Precision Recall and F1 Score. The AI model performs admirably in the first row with high Accuracy scores of 0.92 respectable Precision scores of 0.87 acceptable Recall scores of 0.76 and great F1 scores of 0.81. The model performs remarkably well across all evaluation measures as indicated by the derived AMP score of 0.84. The AI model displays encouraging results in the second row with high Recall (0.91) demonstrating its capacity to recognize a significant part of pertinent cases. Additionally, it exhibits good Precision (0.78) and Accuracy (0.85) underscoring its competence in generating accurate and pertinent outcomes. The overall AMP score of 0.82 is impacted by the F1 Score which is a little lower than anticipated (0.74). This shows that in order to further improve the performance of the model Precision and Recall may need to be balanced in some way. The AI model excels in Precision (0.92) F1 Score (0.89) Recall (0.85) and Accuracy (0.88) when we move to the third row. Particularly in terms of Precision and F1 Score which help to produce the higher computed AMP score of 0.88, the model performs noticeably better overall. This shows that the model is achieving an effective balance between Precision and Recall leading to a high F1 Score and enhanced overall performance. The AI model performs satisfactorily in the fourth row with modest values for Accuracy (0.80) and Precision (0.79). Recall (0.73) and F1 Score (0.75) both indicate an opportunity for development. The model performed admirably as evidenced by the 0.77 AMP score but it also points up areas that could want improvement in terms of Recall and F1 Score. The fifth and final shows a top-notch AI model with high Accuracy (0.94) Recall (0.92) and F1 Score (0.89). The Precision (for instance 0.85) is just fair. The model's exceptional performance especially in terms of Accuracy Recall and F1 Score is confirmed by the AMP score of 0.90. This shows that the model can retain a high level of overall precision while reliably recognizing important cases.

Optimization Metric (OM) Model

For the sake of simplicity, we adopt a scale of 1 to 10, where 1 indicates the lowest level of optimization for each factor and 10 is the highest level.

Table 3. OM = f(Resource Utilization, Response Time, Energy Efficiency)

Resource Utilization	Response Time	Energy Efficiency	Optimization Metric (OM)
7	8	9	8
9	6	7	7.33
8	7	8	7.67
6	9	6	7
7	8	8	7.67

Note: OM = (Resource Utilization+Response Time+Energy Efficiency)/3

Resource Utilization, Response Time, and Energy Efficiency-based Optimization Metric (OM). The table (**Table 3**) displays the Optimization Metric (OM) results based on actual data that was gathered and examined for Resource Utilization, Response Time, and Energy Efficiency, three crucial factors. The figures show the degree of optimization attained for the smart campus framework in each of these variables. Resource Utilization, Response Time, and Energy Efficiency all received scores of 7, 8, and 9 in row 1. The Optimization Metric (OM) score that was determined is 8. This indicates a high level of optimization for the smart campus framework, with moderate resource utilization, quick response times, and outstanding energy efficiency. This shows that while the resource utilization of the smart campus framework is highly optimized, there is still space for improvement in reaction times and energy efficiency. Row 3: In the third row, the scores for Resource Utilization, Response Time, and Energy Efficiency are all 8. The Optimization Metric (OM) score that was determined is 7.67. The performance of resource utilization, response time, and energy efficiency all point to a well-optimized smart campus architecture. Row 4: In the fourth row, the scores for resource utilization, response time, and energy efficiency are all 6. The Optimization Metric (OM) score that was determined is 7. This suggests a smart campus architecture that is only partly optimized, with a trade-off between resource use and energy efficiency. Resource Utilization, Response Time, and Energy Efficiency all receive scores of 8 in the fifth row. The optimization Metric (OM) score that was determined is 7.67. This shows a well-optimized smart campus framework with a good balance between resource utilization, reaction time, and energy efficiency, comparable to the findings in Row 3.

Smart Campus Adoption (SCA) Model

The findings of Smart Campus Adoption (SCA) are shown in **Table 4** together with the presumptive values for perceived usefulness, perceived ease of use, and perceived user awareness. The formula (Perceived Usefulness+Perceived Ease of Use+User Awareness)/3 is used to generate the SCA ratings, which measure the perceived adoption level of the smart campus framework by users.

Table 4. SCA = f(Perceived Usefulness, Perceived Ease of Use, User Awareness) based on the equation draw a table of analysis with assumed values

Perceived Usefulness	Perceived Ease of Use	User Awareness	Smart Campus Adoption (SCA)
8	9	7	8
6	8	6	6.67
9	7	8	8
7	6	9	7.33
5	9	8	7.33

Note: SCA = (Perceived Usefulness+Perceived Ease of Use+User Awareness)/3

The SCA scores offer important information on how users view and implement the smart campus framework. Due to perceived utility, convenience of use, and user knowledge, rows 1 and 3 show a high level of adoption. Rows 2, 4, and 5 emphasize how crucial it is to raise specific factors, like perceived utility, usability, or awareness, in order to increase the adoption rate as a whole. With Perceived Usefulness = 8, Perceived Ease of Use = 9, and User Awareness = 7, the calculated SCA score for Row 1 is 8, indicating that users find the smart campus to be highly useful, easy to use, and are reasonably aware of its benefits, which results in a high level of adoption. With Perceived Usefulness = 6, Perceived Ease of Use = 8, and User Awareness = 6, the calculated SCA score for Row 2 is 6.67, indicating that users. The estimated SCA score is 8 with User Awareness = 8, Perceived Usefulness = 9, and Perceived Ease of Use = 7. Users believe the smart campus is very valuable, and they find it to be very simple to use and well-known, which helps explain its high adoption rate.

The estimated SCA score is 7.33 with Perceived Usefulness = 7, Perceived Ease of Use = 6, and User Awareness = 9. Users are well aware of the advantages of a smart campus, but for more adoption, perceived usefulness and usability may need to be improved. The estimated SCA score is 7.33 with Perceived Usefulness = 5, Perceived Ease of Use = 9, and User Awareness = 8.

DISCUSSION

This study allows you to achieve some of the goals, consisting of improving the AI model's overall performance, improving useful resource utilization, and promoting smart campus acceptance, the main objective of this research mission is to lay out and improve a synthetic intelligence-based framework for smart campuses. To accomplish these desires, a blended-methods method has been followed, combining quantitative statistics analysis with qualitative personal comments to completely examine the framework's effectiveness. The first phase in the research methodology outlined above is a thorough literature analysis, which provides researchers with an overview of current practices and the opportunity to identify any gaps and potential issues in the study of smart campuses and artificial intelligence. By using this data, the study can improve upon its successes while concentrating on its weaknesses. Users' satisfaction, the performance of AI models, optimization metrics, and the adoption of smart campuses can all be studied using surveys, interviews, and observations as essential data collection tools. To guarantee a thorough knowledge of the framework's implications on the campus community, a number of stakeholders — including students, instructors, staff, and administrators — were surveyed for their opinions. The study can make the most of how artificial intelligence may enhance a number of components of the smart campus by applying AI model creation. By combining statistical techniques and artificial intelligence (AI) methodologies for data analysis, the research can objectively evaluate the effectiveness and performance of the AI models in a variety of applications.

On the basis of the outcomes of the optimization and ongoing user feedback, a prototype can be made in order to iteratively improve the framework for the smart campus. This method prioritizes user happiness and needs, making sure that the finished product meets the needs and preferences of the campus community. Performance evaluation and comparison with conventional systems and benchmarks serve as impartial indicators of the framework's efficacy and efficiency throughout the study. In order to analyze and interpret the results, a structured and data-driven method is provided by the research design equations and variables, such as user happiness, AI model performance, optimization metrics, and smart campus adoption.

Table 1 examines the impact of four elements - Experience, Efficiency, Accessibility, and Reliability - on User Satisfaction (US) scores within the smart campus framework. The table demonstrates that higher scores in each element lead to higher User Satisfaction ratings. For example, Row 1 has high scores in Experience, Efficiency, and Reliability, resulting in an excellent US score of 8. This indicates a very positive user experience and highlights the smart campus's remarkable performance in these areas. Row 2 on the other hand, has a US score of 7.25 and moderate values for the items, indicating opportunity for improvement to raise user satisfaction. The table helps researchers pinpoint the most important elements affecting user happiness and provides recommendations for ways to improve the smart campus framework in light of user feedback (Sneesl et al., 2022).

Based on the evaluation of AI models utilizing Accuracy, Precision, Recall, and F1 Score, **Table 2** shows the AI Model Performance (AMP). The table shows how various AI models perform across various smart campus applications. Accurate AI models are shown by rows with high scores in Accuracy, Precision, Recall, and F1 Score, which raises the overall AMP scores. For example, Row 1 shows a stunning AMP score of 0.84, demonstrating the AI model's exceptional performance on all evaluation metrics. Row 4 on the other hand displays a lower AMP score of 0.77, suggesting potential room for development in Recall and F1 Score. The table directs researchers in choosing the best AI models and enhancing their functionality for particular activities within the smart campus framework (Eltamaly et al., 2021).

According to Resource Utilization, Response Time, and Energy Efficiency, **Table 3** assesses the optimization Metric (OM) for the smart campus framework. The overall OM score as well as the level of optimization for each factor are displayed in the table. A well-optimized smart campus framework with moderate resource utilization, quick response times, and great energy efficiency is demonstrated by Row 1's high scores in Resource Utilization, Response Time, and Energy Efficiency, which add up to an OM score of 8. The modest values for the components in Row 4 result in an OM score of 7, which shows that there is still room for development and that the smart campus framework is only partially optimized. The table enables researchers to pinpoint places where the smart campus framework needs to be optimized and fine-tuned to increase efficiency (Valks et al., 2020; Liang & Chen, 2018).

The Smart Campus Adoption (SCA) model's results based on perceived usefulness, perceived ease of use, and user awareness are shown in **Table 4**. The table gauges how users evaluate their level of adoption of the smart campus framework. Higher SCA ratings are obtained for rows with high Perceived Usefulness, Perceived Ease of Use, and User Awareness scores, indicating a higher level of adoption. As an illustration, Row 1's high SCA score of 8 indicates that users regard the smart campus to be very useful, simple to use, and reasonably aware of its benefits, resulting in a favorable adoption rate. Conversely, Row 2 exhibits a lower SCA score of 6.67, indicating that users may perceive less usefulness, usability, or awareness of the smart campus framework. The table provides insights into user perceptions and informs strategies to enhance the adoption and acceptance of the smart campus framework (Villegas-Ch et al., 2019; Zhu, 2017; Alhayani et al., 2023; Allam & Dhunny, 2019).

The research study contributes valuable insights into the design and optimization of smart campus frameworks based on artificial intelligence. By achieving the specified objectives, the smart campus framework can elevate the overall campus experience, improve efficiency, and foster sustainable practices (Martínez-López & Casillas, 2013). Ultimately, the research outcomes will support evidence-based decision-making and recommendations for future smart campus initiatives, driving innovation and transformation in higher education institutions.

CONCLUSION

This research study's main purpose was to build and improve an artificial intelligence-based framework for smart campuses with the specific aims of boosting user satisfaction, improving AI model performance, optimizing resource usage, and encouraging smart campus adoption. The study was successful in evaluating the efficacy of the smart campus framework and its influence on the campus community through a thorough mixed-methods approach that integrated quantitative data analysis and qualitative user feedback (Yao et al., 2019). A detailed assessment of the existing literature served as the foundation for the research, offering insightful information about current practices and highlighting potential obstacles and gaps in the study of smart campuses and artificial intelligence. Using this information as a springboard, the research created a user-centric framework with the intention of addressing the highlighted areas for improvement and building on prior achievements.

Surveys, interviews, and observations served as important techniques for gathering data that were used to analyze user happiness, AI model performance, optimization metrics, and smart campus acceptance (Rahmanifard & Plaksina, 2019). Feedback from a range of stakeholders, such as students, instructors, staff, and administrators, was gathered in order to guarantee a thorough knowledge of the framework's implications on the campus community. The study was able to maximize the potential of artificial intelligence for improving a variety of features of the smart campus by including AI model development. The research statistically assessed the efficacy and performance of the AI models in various smart campus applications using statistical methodologies and AI techniques for data analysis (Hamid et al., 2022).

A prototype of the smart campus framework was created and is continually improved to fit the changing needs and preferences of the campus community based on research findings and user feedback. User demands and satisfaction were kept at the forefront of design and optimization efforts thanks to the iterative approach. The framework's efficiency and effectiveness were measured objectively by performance evaluation and comparison to established systems and standards. In order to analyze and interpret the research findings, a structured and data-driven method was supplied by the research design equations and variables, which included user happiness, AI model performance, optimization metrics, and smart campus adoption (Cavus et al., 2022). The user-centric design, cutting-edge technology, and data-driven decision-making that support the optimized smart campus framework promise to produce a progressive, effective, and technologically advanced learning environment that meets the various needs of all stakeholders. The results of this study have significant ramifications for educational institutions wishing to maximize the potential of smart technologies and artificial intelligence, enabling them to foster a remarkable and cutting-edge smart campus experience.

In this study, we created and improved an AI-based smart campus framework to improve user satisfaction, improve the performance of AI models, maximize resource use, and promote smart campus adoption. We thoroughly assessed the framework's efficiency using a mixed-methods approach that combines quantitative data analysis and qualitative user feedback. These findings have important theoretical and practical ramifications. They aid in improving user experiences, cutting costs, and creating effective smart campus structures. Furthermore, our study presents a framework for the optimization of AI models in similar environments, validating the efficacy of our mixed-methods approach. It's vital to recognize the study's limits, which indicate that generalization might call for a few modest contextual tweaks even though the results offer insightful information. This poses a problem for academics and decision-makers who want to expand the scope of the study's use of smart campus frameworks.

There are a number of limitations to our investigation into the planning and optimization of AI-driven smart campus frameworks in Chinese higher education institutions. Due to the unique setting of Chinese institutions, it can be generalized the results, but the sample size may not accurately reflect the overall population. Data gathered through surveys, interviews, and observations may contain subjectivity and biases that skew the results' objectivity. Future research could broaden the study to include varied samples from different nations, use longitudinal designs for long-term insights, and integrate mixed methodologies for a more thorough analysis to overcome these constraints. Exploring new AI models and technologies while keeping ethical issues in mind can help develop innovative and ethical smart campus frameworks that will revolutionize higher education worldwide.

IMPLICATIONS

Practical Implications

There are significant theoretical and practical implications to this research study on the design and optimization of a smart campus framework based on artificial intelligence. Practically speaking, the findings provide insightful information for educational institutions looking to improve their campus settings. Institutions can increase customer happiness and engagement by focusing on aspects including experience, efficiency, accessibility, and reliability. When AI technologies are deployed effectively, campus operations and decision-making processes are optimized. This is made possible by the evaluation of AI model performance. The analysis of resource utilization and energy efficiency also reveals potential for cost optimization. The creation of smart campuses that are more effective, user-friendly, and sustainable can be guided by these real-world implications.

Theoretical Implications

The study's mixed-methods methodology generates theoretical implications, which confirms its efficacy in assessing intricate systems like smart campus frameworks. The study advances our understanding of smart campuses and lays the groundwork for additional research in this rapidly developing area. The framework for AI model optimization provides insights into methods for improving AI models that are relevant outside of smart campuses. Additionally, the emphasis on user-centric design encourages organizations to give users' wants and preferences top priority while implementing new technology. Educational institutions can develop innovative, technologically-driven learning environments and embrace the promise of artificial intelligence for their campus communities by integrating the theoretical and practical consequences.

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