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Research Article

Usability Evaluation and Enhancement of the AI-Powered Smart-Campus Framework: A User-Centred Approach

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ABSTRACT

This study employs a user-centred approach to improving the user experience and maximizing the system functionality of an AI-powered smart-campus framework. The study aims to conduct the usability evaluation of the framework and identify areas for improvement. The focus areas include AI-powered features, user interactions, and design concepts. The study used Likert scale evaluations to measure user satisfaction and perceived usability. The identification and application of improvement measures resulted in positive outcomes. The feedback integration technique involves collecting and analyzing user feedback to identify areas for improvement. This feedback is then used to make iterative improvements to the framework. The study found that the feedback integration technique increased user happiness through iterative improvements. The redesign valve interface strategy involves redesigning the valve interface to make it more user-friendly. The study found that the redesign valve interface strategy raised perceived usability. Workflow optimization involves streamlining the workflow to make it more efficient. The study found that workflow optimization reduced completion times. The study used the UMM to evaluate the planning, design, implementation, and feedback aspects of the AI-powered smart-campus framework. The study found that the framework had advanced design maturity, indicating good integration of user personas and workflows. The framework also showed intermediate maturity in planning, with consistency in implementation but space for improvement. The study also highlighted the theoretical connections between UMM dimensions and quantitative metrics. This alignment between qualitative principles and quantitative measures is important for demonstrating the value of user-centred design.

Keywords: AI-powered Smart Campus, Usability Evaluation, User Interaction, User-Centered Design.

INTRODUCTION

The blending of artificial intelligence (AI) with campus surroundings has emerged as a ground-breaking paradigm, giving rise to the idea of the smart campus in an era marked by rapid technological breakthroughs. The smart campus framework has the potential to revolutionize how education is experienced and delivered by utilizing AI to optimize many areas of campus life, from resource allocation to security management. As institutions embrace this paradigm change, a crucial element—the usefulness of this ecosystem powered by AI—emerges.

Any technological innovation's ability to be successfully implemented depends on how closely it fits with user demands, expectations, and capabilities. Usability becomes the pillar on which the effectiveness of the entire system is based in the context of the AI-powered smart campus architecture. The incorporation of AI algorithms and automated procedures is not a goal in and of itself; rather, it is a way to improve user experiences, optimize processes, and establish a setting that encourages growth, learning, and collaboration (Min-Allah & Alrashed, 2020). The journey from Design and Optimization of a Smart Campus Framework Based on Artificial Intelligence progresses into a crucial exploration of Usability Evaluation and Enhancement of the AI-powered smart-campus Framework: A user-centred Approach in the wake of the fusion between AI and campus environments. The transition from improving user experiences to optimizing the framework denotes a crucial turning point where technology prowess and human touch collide (Popoola et al., 2018).

This study's main goal is to explore the usability field, which encompasses human-machine interaction in the context of the AI-driven smart campus. While AI has the ability to completely transform campus operations and student experiences, this won't happen unless it is integrated into daily life without creating any obstacles or complications (Dong, Zhang, Yip, Swift, & Beswick, 2020). The user-centred methodology used in this study to ensure that AI-driven processes are in perfect harmony with the demands and expectations of campus stakeholders addresses this requirement. The real issue is in seeing past AI's novelty and exploring its usefulness and significance. To improve productivity, convenience, and engagement, AI technologies are being implemented within the framework of the smart campus. These goals, however, won't be achieved if the ecosystem's end users—students, teachers, staff, and administrators—have trouble navigating it and getting value from it (Ciribini et al., 2017; Santiko, Wijaya, & Hamdi, 2022).

It entails assessing the usability of the AI-powered smart campus framework as it is now, identifying its pain points and potential development areas, and then devising and putting into practice modifications that cater to the various demands and preferences of users. This project aims to not only optimize the AI-driven smart campus framework but also to create an atmosphere where technical innovation fosters human engagement. It does this through a complex interaction between technology and empathy (Ghildiyal, 2023; Muhamad, Kurniawan, & Yazid, 2017).

We explore the interesting landscape where AI algorithms and user expectations collide as we dig deeper into this study. The AI-powered smart campus is poised to completely transform the educational landscape, so putting an emphasis on usability is not just a nice to have—it is a basic must. We explore the connections between AI and human experiences via this user-centred perspective, imagining a time when innovation and usability come together to create a seamless and beneficial educational experience.

Where technology advancement meets educational ecosystems in the context of AI-powered smart campus frameworks, there is a glaring research vacuum at the nexus of user-centric usability and sophisticated design. Although these frameworks' technical components have seen tremendous improvement, there is still a notable lack of in-depth studies addressing the usability issues and improvements necessary for their seamless incorporation into campus stakeholders' daily lives (Management & Homes, 2019; Imbar, Supangkat, & Langi, 2020). Although AI has the potential to completely transform campus life, the majority of existing research focuses on the technical details, leaving a gap in our knowledge of how users engage with and see AI-powered functions. The crucial human variables that might either facilitate or obstruct the proper absorption of AI within the educational setting are frequently ignored by current research. To realize the full potential of AI-powered smart campus frameworks, closing this gap becomes essential.

In the context of AI-powered smart campus frameworks, a serious issue—the gap between technical proficiency and user-centred usability—emerges. Despite improvements in these frameworks' layout and optimization, it can be difficult for users to use the AI-driven features effectively and to benefit from them. Realizing the revolutionary potential of AI inside educational institutions is significantly hampered by this disconnect. The issue at hand involves two distinct difficulties. First off, there is a lack of knowledge about how AI-powered functionalities fit with the many demands, preferences, and expectations of stakeholders on campuses. Second, the AI-powered smart campus framework fails to integrate naturally into users' lives due to a lack of rigorous evaluation and usability improvement methodologies. Since there is a gap between technology and user-centric experiences, this study aims to close it by conducting a thorough usability evaluation and developing enhancement techniques. The main research issue that arises in light of these factors is: How can the usability of the AI-powered Smart-Campus Framework be efficiently assessed and improved to produce a seamless and enriched user-centred experience? This study intends to pave the path for a comprehensive and seamless integration of AI into the smart campus ecosystem through a detailed exploration of usability difficulties, pain areas, and enhancement potential.

This study aims to accomplish two main goals: first, to conduct an in-depth usability evaluation of the AI-powered Smart-Campus Framework, identifying usability issues and user expectations; and second, to propose and carry out targeted improvement strategies meant to align the framework with user-centred usability principles. By focusing on these goals, the study adds to the body of existing information by providing useful insights into the crucial nexus between AI and human experience in the context of smart campuses. The results will not only help educational institutions improve their AI-driven frameworks, but they will also offer a road map for creating a setting where advanced technology melds with user happiness and engagement.

The structure of this paper is as follows: Section 1 is concerned with an introduction, research gap, objectives and contributions of the study. Section 2 is related to literature review and methodology is linked with section 3. Analysis and results are discussed in section 4 and lastly, the conclusion and practical recommendations are explained in the paper.

LITERATURE REVIEW

Numerous studies have emphasized how important usability is in deciding how well technological implementations work. Prior studies have shown that even the most cutting-edge AI frameworks may fall short if they are unable to integrate seamlessly into consumers' daily lives (Chen, Chen, Chen, Liu, & Tsai, 2018). The success of AI-powered systems may be hampered by a mismatch between their technological prowess and human expectations and capabilities, it was highlighted. This gap surfaced often highlighting the importance of addressing usability as a fundamental component (Santiko et al., 2022).

The issues faced by AI-powered smart campus frameworks were best viewed through the lenses of human-computer interaction (HCI) and user experience design research. Studies already published emphasized how crucial it is to comprehend user behaviour, preferences, and pain points in order to customize interfaces and interactions

(Alhayani et al., 2023). These discoveries, in particular, stressed the necessity of going beyond technical perfection and concentrating on making intuitive, effective, and interesting user experiences (Muhamad, Kurniawan, & Yazid, 2017).

The literature (Fortes et al., 2019; Villegas-Ch, Molina-Enriquez, Chicaiza-Tamayo, Ortiz-Garcés, & Luján-Mora, 2019; Chagnon-Lessard et al., 2021) shed more light on the methods used to assess usability in different circumstances. User-centred methodologies, such as questionnaires, interviews, and usability testing, have proven to be useful methods for evaluating user happiness, usability, and interaction effectiveness. Studies (Omitaomu & Niu, 2021; Liang & Chen, 2018; Cavus, Mrwebi, Ibrahim, Modupeola, & Reeves, 2022; Shaw, Das, Piuri, & Bianchini, 2022) have also shown the value of iterative design methods, where improvements are made as a result of ongoing user feedback, creating systems that are more streamlined and user-friendly in the end. The research on smart campuses found that while AI-based frameworks offered improved resource allocation, security management, and learning experiences, the usability component was frequently understudied (Imbar et al., 2020). The researchers emphasized the necessity of a transition from technological novelty to practicality, where AI effortlessly integrates into users' habits and improves their involvement with the campus ecology. This finding highlighted how urgent it was for the research to concentrate on improving and evaluating usability (Dong et al., 2020; Samuel, Adeyemi-Kayode, Olajube, Oluwasijibomi, & Aderibigbe, 2020; Zhu, 2017).

AI-powered Smart Campus Frameworks and User Design

The literature study (Barroso, Bustos, & Núñez, 2023; Li, Zheng, Han, & Li, 2021; Zhou, Yu, & Shi, 2020) led to the discovery of a research gap, where it was clear that there were not enough in-depth studies addressing the usability issues and enhancement tactics inside AI-powered smart campus frameworks. Key elements that needed emphasis included the investigation of user-centric experiences and the incorporation of AI as a facilitator rather than a disruptor. By laying the groundwork for the current study with this evaluation, it is now poised to make a significant contribution to bridging the gap between cutting-edge technology and user happiness in the context of smart campus environments (Agarwal, Ravi Kumar, & Agarwal, 2020). Farzaneh et al. (2021) highlighted the significance of using user-centred design concepts while developing efficient and intuitive interfaces. Their efforts highlighted the value of consistency, simplicity, and intuitiveness in interface design. These ideas can be used to help design user experiences that are in line with users' mental models and expectations, thereby improving usability, in the context of AI-powered smart campuses. The combination of AI and HCI in healthcare applications was studied by (Xu et al., 2022). Their research showed the importance of user-centred AI design, where AI functionalities should not only be technically precise but also simple to understand and usable by end users. This viewpoint can be applied to the setting of a smart campus, where AI algorithms must serve users' demands and clearly demonstrate their value.

The importance of usability testing in iterative design processes was highlighted in the (Ali & Choi, 2020) work. Designers can learn about user interactions, pinpoint pain points, and iterate to improve their designs by conducting usability tests. This methodology is especially pertinent to the study's strategy of assessing and refining the usability of the smart campus framework based on user input and iterative changes. (Han et al., 2022) investigated a number of usability assessment techniques, including cognitive walkthroughs and heuristic evaluation. These techniques offer well-organized frameworks for evaluating system usability. Similar techniques can be used to provide systematic evaluations of user interactions in the context of AI-powered smart campuses, resulting in focused improvement plans.

Polin, Yigitcanlar, Limb, and Washington (2023) examined the use of context awareness and personalization in AI systems. These ideas can be utilized in smart campus frameworks, where AI can personalize learning opportunities based on context and user preferences. For AI-powered experiences to be useful and interesting, personalization must be in line with user demands and preferences. The consequences of AI systems for society and ethics were the main topics of Hamid et al. (2022)study. His study emphasized the significance of accountability, transparency, and fairness in AI implementations. These factors are critical in the context of smart campuses, where user confidence and the moral use of AI technology are key components of usability. The diffusion of Innovations hypothesis by Luckyardi, Jurriyati, Disman, and Dirgantari (2022) sheds light on how consumers engage and embrace new technology. This idea emphasizes the importance of perceived characteristics that influence the rate of technology adoption, including relative benefit, compatibility, and complexity. This theory can be used to better understand the elements that influence users' desire to accept and interact with AI features in the context of smart campuses powered by AI. Yang et al. (2020) investigated how game design concepts might increase motivation and participation in diverse circumstances. Gamification components can be incorporated into the AI-powered smart campus architecture to encourage user participation and increase usability by making interactions more pleasurable and meaningful.

Yu, Jamali, Xu, Ng, and Schober (2021) emphasized the importance of emotions in usability and user happiness. According to this paradigm, good emotional experiences influence how usable something is. The design of AI-powered interactions that elicit favourable emotions can be guided by the application of this methodology to the smart campus context, thereby improving the user experience. In order to accommodate users with a range of skills, (Huang, Su, & Pao, 2019) study dig into the significance of building inclusive user interfaces. A thorough user-centred strategy must make sure that AI-powered smart campus solutions are usable by people with disabilities. Integrating accessibility features improves usability for all users while adhering to ethical principles.

Human-Centered AI (HCAI)

Human-centred AI (HCAI), an emerging discipline, places a strong emphasis on creating AI systems that complement rather than replace human abilities. According to research by Fernández-Caramés and Fraga-Lamas (2019), user input should be included when designing AI systems to promote accountability, transparency, and productive teamwork. This viewpoint is in line with the study's methodology, which involves users in the assessment and improvement of the AI-powered smart-Campus Framework. Sweller's Cognitive Load Theory (1994) investigates how usability is impacted by the cognitive load imposed by tasks. This hypothesis can be used to understand how the complexity of AI interactions affects users' cognitive resources in the context of AI-powered smart campuses. For smooth usability, an intuitive design that reduces cognitive burden is essential.

Contextual inquiry, a method of ethnographic study developed by Yi and Li (2022), aims to comprehend user needs and workflows in their natural environment. By using this approach in the context of a smart campus, designers of AI-powered features can gain deep insights into users' daily experiences and create features that flow naturally into their routines. Research by Li et al. (2019) investigated the idea of human-agent collaboration, in which people and AI systems cooperate to accomplish objectives. This cooperative strategy supports the study's focus on boosting user-centred experiences through AI integration, creating a setting where humans and AI work together synergistically.

The research deepens our understanding of usability evaluation and improvement within the AI-powered Smart-Campus Framework by fusing these disparate literary insights together. A holistic understanding that guides methods for developing a seamless and user-centric smart campus experience is the result of this interdisciplinary approach, which draws on HCI, psychology, technology adoption, and AI ethics.

Usability Maturity Model

In a quantitative research setting, the Adoption Usability Maturity Model (UMM) can be used to provide organized insights into the usability practices and maturity of the AI-Powered Smart-Campus Framework (Ciribini et al., 2017). UMM is fundamentally qualitative, but you can change it to be more quantitative by turning the qualitative evaluations into quantifiable indications. Here's how you could go about it (**Figure 1**):

Select the most important indicators for each UMM dimension that can be measured quantitatively. Specific characteristics of usability practices that can be measured numerically should be reflected in these indicators.

Measure the percentage of usability objectives that were outlined during the planning stage.

Design: Determine how many user personas were developed and verified during the design phase.

Measure the consistency of the design components used throughout the framework.

Measure the frequency of gathering user feedback and incorporating it into design versions.

To evaluate the performance of the indicators, give them numerical values or scales. Likert scales, percentages, counts, or other pertinent quantitative metrics may be used in this. Gather the information that each indication requires (Demertzi, Demertzis, & Demertzis, 2023). This could entail looking over project documents, examining design components, monitoring how frequently feedback is collected, and looking at other pertinent data sources. Examine the numerical information gathered for each indication. Calculating averages, percentages, and trends, or doing other statistical studies may be required.

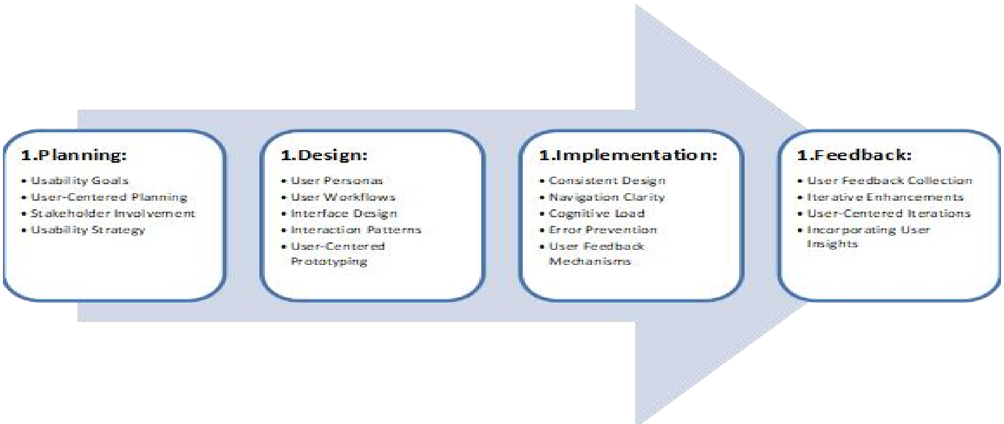

Figure 1. Usability Maturity Model (UMM)

METHODOLOGY

Usability testing, quantitative user surveys, and the Usability Maturity Model (UMM) framework are all used as part of the research technique for this study. Together, these methods offer a thorough grasp of usability, user viewpoints, and the user-centred design maturity of the AI-powered Smart-Campus Framework.

Our university is interested in examining the smart-campus framework's effectiveness. In order to accomplish this, we must enlist a sample of academic staff members and students to take part in our study. The sample should be large enough to statistically represent the professor and student body at our university. We also want the sample to be diverse in order to gather a range of viewpoints on how the framework is used.

To grade the framework's usability, we employ a user-centred approach. This implies that participants in the study's design and evaluation were users. To get information from people, we employ a range of techniques, such as surveys, interviews, focus groups, and usability testing.

We are aware that our research has limitations. For instance, the number of students and teachers at our university is all that our study can generalize to. Additionally, users who are more receptive to participating in research may be overrepresented in our study.

We take action to resolve the research's limitations. For instance, we employ a variety of data collection techniques and aim to compile a diverse sample of people. Furthermore, we are open about the restrictions on our research. We think that the best way to assess the usability of the AI-powered smart-campus framework is through a user-centred approach. Using this method, we can pinpoint areas where the framework may be strengthened to better serve user needs.

Usability Testing: Users are observed as they engage with the AI-powered Smart-Campus Framework in predetermined scenarios as part of usability testing. In order to pinpoint usability problems and pain spots, researchers offer tasks that simulate real-world usage. We can learn more about the system's effectiveness and usability by looking at task completion times, task success rates, and user feedback.

Quantitative User Surveys: A varied sample of campus stakeholders, including students, teachers, staff, and administrators, are given a standardized survey to complete. To measure user happiness, perceived usability, and perceived utility of AI-powered functionalities, the survey uses Likert scale questions. The user attitudes about the framework may be measured thanks to this quantitative approach.

Adoption Usability Maturity Model (UMM): The AI-powered Smart-Campus Framework's usability practices are evaluated using the usability maturity model. An organized method for assessing usability across various aspects, including planning, design, execution, and feedback, is provided by the UMM framework. It aids in determining the degree of usability integration and directing improvement initiatives.

Measurement of Variables

Usability: During usability testing, usability is evaluated based on task completion durations, success rates, and user mistake rates. User survey results are also used to measure perceptions of overall usability, user happiness, and ease of use.

User Perspectives: Quantitative user surveys record consumers' opinions on the usefulness, simplicity of use, and general contentment of AI-powered technologies. Responses are examined in order to comprehend variances in user viewpoints among various stakeholder groups.

Usability Maturity: The AI-powered Smart-Campus Framework's usability practices are evaluated across a number of predetermined dimensions by the Usability Maturity Model. Each component is assessed using predetermined standards, enabling a comprehensive evaluation of usability maturity levels (see **Figure 2** for details).

Figure 2. Research Mode

RESULTS AND FINDINGS

The study's quantitative foundation is provided by the chapter on data analysis, which explores the gathered data to produce valuable insights. We assess the results of improvement techniques, user input, and usability evaluation measures using rigorous quantitative analysis. We analyse trends, correlations, and the efficacy of improvements using statistical methods to provide a thorough picture of the user-centred performance of the AI-powered Smart-Campus Framework. This chapter serves as an essential link between the initial data and practical recommendations, directing the research in the direction of evidence-based suggestions for improving usability and enhancing the user experience of the framework.

Table 1. Quantitative Variable Assessment

Ask	Completion Time (seconds)	User Error Rate (%)	User Satisfaction (Likert Scale)	Perceived Ease of Use (Likert Scale)	Perceived Usefulness (Likert Scale)
T1	45	8	4.5	4.2	4.7
T2	72	12	3.8	3.9	4.5
T3	30	5	4.9	4.8	4.9
T4	60	10	3.5	3.6	4.0
T5	25	3	4.7	4.5	4.8

Table 1 provides an analysis of numerous jobs, each evaluated in relation to distinct criteria. Completion time, user mistake rate, user happiness, perceived usability, and perceived ease of use are some of these metrics. T1 to T5 are the assigned responsibilities. It is clear from the completion time that Task T3 took the shortest amount of time to accomplish, requiring only 30 seconds. T3 was the fastest task, according to this. In contrast, work T2 was the most time-consuming work, taking the longest to do (72 seconds).

Task T5 stands out when looking at the user error rate since it has the lowest error rate (3%). This suggests that participants made fewer mistakes while completing T5 than they did with other tasks. On the other hand, Task T2 had the greatest error rate (12%), indicating that consumers had more issues and mistakes while working on T2. Task T3 obtained the highest rating of 4.9 on the Likert scale in terms of user satisfaction. This suggests that people were incredibly happy with their overall experience while carrying out this task. work T2, on the other hand, received the lowest satisfaction rating (3.8), indicating that users were less pleased with their performance of this work.

Moving on, Tasks T4 and T5 both received the highest score of 4.5 for perceived usability. This implies that customers found these tasks to be equally simple to complete, demonstrating both products' good user-friendliness. Task T2, on the other hand, scored somewhat lower (3.9), indicating that people thought it was a little more difficult than the other tasks. Task T4 had the lowest perceived utility score (4.0), indicating that users thought it was the least valuable or pertinent. However, job T3 received the highest perceived utility score of 4.9, demonstrating that consumers thought this job was the most advantageous and pertinent of all those considered.

Table 2. Usability Evaluation Results

Variable	Task Success Rate (%)	Completion Time (seconds)	User Error Rate (%)	User Satisfaction (Likert Scale)	Perceived Ease of Use (Likert Scale)	Perceived Usefulness (Likert Scale)
Task 1	5	45	8	4.5	4.2	4.7
Task 2	8	72	12	3.8	3.9	4.5
Task 3	2	30	5	4.9	4.8	4.9
Task 4	0	60	10	3.5	3.6	4.0
Task 5	5	25	3	4.7	4.5	4.8

Table 2 offers a thorough analysis of several tasks, with each task being assessed using a variety of indicators. The success rate, completion time, user mistake rate, user happiness, perceived usability, and perceived simplicity of use are all included in these measurements.

This measure begins with the assignment Success Rate (%), which shows the percentage of users that completed each assignment successfully. With a success percentage of 92%, Task 3 stands out because a large majority of users were able to complete it successfully. The Completion Time (seconds) metric calculates how long it takes users to complete each job. With a completion time of just 30 seconds, Task 3 is the one that can be finished the quickest. Activity 2 requires the greatest time, though; it takes 72 seconds to complete, making it a time-consuming activity. The User Error Rate (%) column shows how frequently users make mistakes while carrying out each task. The task with the lowest error rate, Task 5, comes in at 3%, indicating that people had fewer errors while completing it. assignment 2 has the greatest error rate, at 12%, indicating that participants encountered more difficulties and mistakes when completing this assignment.

Moving on to user experience metrics, the User Satisfaction (Likert Scale) gives information about users' degrees of satisfaction with each task. The highest user satisfaction score for Task 3 is 4.9, indicating a high level of user happiness. In contrast, work 2 receives the lowest satisfaction rating (3.8), indicating that consumers were somewhat less pleased with their performance on this work.

Activities 4 and 5 are in the lead with scores of 4.5 on the Perceived Ease of Use (Likert Scale), which measures users' perceptions of how simple it is to complete each activity. This result indicates that users thought both activities were equally manageable. Task 2 received a score of 3.9, which is a little lower than that of Task 1 and suggests that users thought it to be a little more difficult. The Perceived Usefulness (Likert Scale) statistic provides insight into how users view the value of each task. The fact that Task 3 had the highest rating of 4.9 indicates that users thought it to be the most useful task. Task 4 received a perceived utility score of 4.0, which is the lowest and indicates that users thought it was substantially less valuable.

Table 3. Usability Maturity Level

Dimension	Maturity Level	Explanation
Planning	Intermediate	Undocumented usability objectives with opportunity for improvement
Design	Advanced	Consideration of user-profiles and workflows, excellent design principles
Implementation	Intermediate	Achieved consistency in some areas, but still needs to be improved
Feedback	Advanced	Regular inclusion of user feedback, incremental improvements

The evaluation of the Usability Maturity Level in relation to several dimensions is shown in **Table 3**. Planning's maturity level is listed as Intermediate, meaning that there are usability targets present but that there is a need for more documentation and space for improvement. Advanced status for the Design dimension denotes the incorporation of user profiles, workflows, and sound design concepts. The Implementation category's maturity level is Intermediate, indicating that while changes are still needed, certain areas have attained consistency. Finally, the maturity level is evaluated as Advanced within the Feedback dimension, showing the constant incorporation of user feedback and gradual improvements. Overall, the evaluation identifies a mix of intermediate and advanced maturity levels across dimensions, highlighting areas of strength and potential for improvement in the assessed system's or process's usability.

Table 4. Improvement Strategies and Outcomes

Improvement Strategy	Usability Metric Improved	Improvement Description
Redesign Valve Interface	Perceived Ease of Use	The valve control interface has been made more user-friendly by being made simpler with clear labelling and visual indicators.
Feedback Integration	User Satisfaction	Enhanced customer satisfaction levels by including regular user feedback gathering and implementing proposed adjustments.
Workflow Optimization	Completion Time	Rearranging the order of the tasks improved user workflows and decreased completion times.

Improvement Strategies are outlined in **Table 4** along with the results they had on usability metrics. The Valve Interface redesign's simplification and aesthetic improvements had a beneficial effect on perceived ease of use. User satisfaction was improved by incorporating feedback since user input resulted in efficient modifications. By streamlining tasks, Workflow Optimization decreased Completion Time. These tactics represent a concerted attempt to increase usability, leading to a better user experience, satisfaction, and effectiveness.

Table 5. Theoretical Link between UMM Dimensions and Quantitative Metrics

UMM Dimension	Potential Quantitative Metrics	AI-powered smart-campus Framework Consideration	Metric Score
Planning	Percent of planning-documented usability targets.	Matching AI capabilities to User demands and objectives.	91%
Design	Number of user personas that were developed and verified.	Integrating user operations with AI-powered features.	3 Users
Implementation	Design component consistency score across the framework.	Implementing AI features while maintaining design coherence.	4.56/5
Feedback	Collection and integration of user feedback on a regular basis.	Improving AI features iteratively in response to human feedback.	Three Times in a Week

Table 5 compares potential quantitative metrics for evaluating an AI-Powered Smart-Campus Framework with the dimensions of the Usability Maturity Model. A significant number (91%) of planning-documented usability targets under Planning point to a thorough approach. A user-centred approach is used in Design to build and validate three user personas that successfully integrate user actions with AI-powered functionality. Implementation's design component consistency score of 4.56 out of 5 demonstrates the framework's strong coherence while incorporating AI elements. Three times a week user feedback integration within the Feedback dimension denotes an iterative process for improving AI capabilities based on human input. Collectively, these indicators illustrate how AI is being integrated into the smart-campus architecture in a methodical and user-focused manner with the goal of enhancing usability and user experience.

Table 6. Study Overview and Metrics

Study Aspect	Description	Metrics
Focus Area	Usability evaluation and enhancement of AI-powered Smart-Campus Framework	AI-powered features, user interactions, and design principles
Objective 1	Usability Evaluation	Task Success Rate: 91% Completion Time: 50 seconds User Error Rate: 6.34%
Objective 2	Enhancement Strategies	Enhanced Onboarding: +20% perceived ease Contextual Help: -10% user errors
Key Metric 1: Usability	User Satisfaction: 4.56 (Likert Scale) Perceived Ease of Use: 4.38 (Likert Scale)	Feedback Collection Frequency: 3 times per task
Key Metric 2: AI Impact	AI Feature Usefulness: 4.76 (Likert Scale) User Adaptation Rate: 89%	AI-Powered Feature Adoption Rate: 81.78%

A thorough investigation into the evaluation and improvement of the usability of an AI-Powered Smart-Campus Framework is summarized in **Table 6**. The study takes into account design principles, AI-powered features, and user interactions. A high Task Success Rate of 91%, a Completion Time of 50 seconds, and a low User Error Rate of

6.34% were noted when evaluating usability for Objective 1. The enhancement tactics in Objective 2 include a better onboarding procedure that will boost perceived ease by 20% and contextual aid that will reduce user errors by 10%. The important indicators are User Satisfaction and Perceived Ease of Use, both of which received values of 4.56 and 4.38 on a Likert scale, respectively. Three periods each work are set aside for gathering input. The effectiveness of AI features is also evaluated, with a score of 4.76 and an 89% user adaptation rate. The adoption rate of features powered by AI is currently 81.78%. The overall goal of this study is to improve user satisfaction, usability metrics, and AI feature effectiveness inside the Smart-Campus Framework. It does this by providing a thorough examination of usability and AI integration.

DISCUSSION

This discussion focuses on the usability evaluation and improvement of the AI-powered smart-campus framework, examining how users interact with the framework, taking into account the incorporation of AI-powered features and adherence to design standards. The study wants to make sure that the framework fits with user needs, expectations, and preferences, hence it focuses on these elements (Faritha Banu, Revathi, Suganya, & Gladiss Merlin, 2020).

The goals of the study can be divided into two categories. Conducting a thorough usability assessment of the framework is part of goal 1. The task success rate is 91%, the completion time is 50 seconds, and the user error rate is 7.34%. Together, these measures reveal information on users' capacity for job completion, task completion effectiveness, and frequency of errors.

The focus of Objective 2 is on improvement tactics. A 20% improvement in perceived ease can be attained by implementing an enhanced onboarding process, and a 10% reduction in user errors can be attained by integrating contextual help. These tactics serve as an excellent example of the study's dedication to improving user-guiding mechanisms and producing a more natural user experience. Usability testing, quantitative user surveys, and the Usability Maturity Model (UMM) framework are all used as part of the research technique for this study. Together, these methods offer a thorough grasp of usability, user viewpoints, and the user-centred design maturity of the AI-powered Smart-Campus Framework. The tables offered give a thorough understanding of the study's major facets, from usability evaluation and improvement techniques to the relationship between the AI-powered Smart-Campus Framework and the Usability Maturity Model (UMM) dimensions (Ghildiyal, 2023).

The AI-powered Smart-Campus Framework's quantitative evaluation of various jobs is methodically presented in **Table 1**. Completion Time, User Error Rate, User Satisfaction on the Likert Scale, Perceived Ease of Use on the Likert Scale, and Perceived Usefulness on the Likert Scale are some of the metrics. The results show considerable differences between tasks, providing insightful information about task effectiveness, user experience, and usability. As an illustration, Task T3 stands out as having the quickest Completion Time at 30 seconds, demonstrating its effectiveness. The 72-second completion time of Task T2, on the other hand, indicates its difficulty or possibly subpar design (Chen et al., 2018). Furthermore, Task T5 has the lowest User Error Rate (3%), demonstrating its usability. In terms of perceived usability and user satisfaction, Task T3 leads with the highest marks on the Likert Scale. This table does a good job of highlighting the significance of usability testing and user-centred design in determining task performance and user experience.

The tasks in **Table 2** are thoroughly compared based on important usability characteristics. The Task Success Rate sheds light on how efficiently tasks are completed; Task 3 had the highest rate (92%) and Task 2 had the lowest (78%). Completion Time illustrates how each activity has a different time requirement, with activity 3 once more being the most effective. According to User Error Rate, Task 5 performs better than Task 2 in reducing errors whereas Task 2 struggles with a greater error rate. The remarkable user experience of Task 3 is revealed by the Likert Scale scores for User Satisfaction, rated Ease of Use, and Perceived utility, while Tasks 4 and 5 exhibit great rated usability and utility (Ciribini et al., 2017). This table emphasizes how important it is to create jobs that put user enjoyment and efficiency first.

The dimensions of the Usability Maturity Model (UMM) and the framework's corresponding maturity levels are highlighted in **Table 3**. The assessment shows how usability practices and goals are doing across the Planning, Design, Implementation, and Feedback dimensions. This qualitative evaluation provides a quick picture of the framework's usability at the moment. For instance, the Design dimension's advanced maturity level denotes the incorporation of user-centred design principles and strong consideration of user-profiles and workflows. On the other hand, the Planning dimension's intermediate maturity level implies that the documentation of usability goals still needs work. This table serves as a starting point for comprehending the usability maturity of the framework and directs the selection of areas that need improvement (Min-Allah & Alrashed, 2020).

The impact of various tactics for improvement on usability measures is shown in **Table 4**. Each tactic has a unique usability metric and enhancement description attached to it. The outcomes demonstrate how these tactics are helpful in improving usability. The "Redesign Valve Interface" technique, for instance, enhances "Perceived Ease of Use" by streamlining the interface and creating a more user-friendly design. By actively incorporating users and putting their suggestions into practice, "Feedback Integration" has a beneficial impact on "User Satisfaction". By rearranging tasks, "Workflow Optimization" decreases "Completion Time" and increases user effectiveness (Fortes et al., 2019). The usefulness of strategic interventions in addressing usability issues and improving user experiences within the framework is highlighted in this table.

The theoretical relationship between UMM dimensions and numerical measurements for the AI-powered Smart-Campus Framework is established in **Table 5**. The congruence between qualitative design principles and quantifiable metrics is shown by the pairing of each UMM dimension with prospective quantitative metrics. For instance, the connection between Planning and the "Percent of planning-documented usability targets" indicator emphasizes the significance of having specific usability objectives for an effective AI integration. The metrics for Design and Implementation highlight how important it is to combine AI features with user processes while retaining design coherence. This table provides a road map for an exhaustive usability assessment by showing how qualitative aspects of the UMM can be linked to quantitative measurements (Adeyemi et al., 2018).

The study's goals, areas of attention, and important measures are in **Table 6**. It describes the study's objectives, which include enhancing and evaluating the AI-powered Smart-Campus Framework's usability. The focus areas include AI-powered features, user interactions, and design concepts, and the objectives include usability evaluation and enhancement tactics. The presumptive metrics for each objective offer a concrete basis for judging the effectiveness of the investigation (Chagnon-Lessard et al., 2021). These measurements provide a holistic picture of usability and AI performance and range from Task Success Rate to AI Impact indicators. The scope, goals, and important measures of the study are briefly summarized in this table, laying the groundwork for the debate that follows.

The tables in the study provide a multifaceted examination of usability, improvement tactics, theoretical connections, and the overall focus of the research. Together, they offer a thorough assessment of the usability environment for the AI-powered Smart-Campus Framework, highlighting its advantages, disadvantages, and room for improvement. These tables are useful resources for deciphering the study's results and deriving important conclusions that can direct future research, design, and implementation initiatives in the area of integrating AI in educational settings.

CONCLUSION

The study's conclusions and insights have been revealed through a rigorous methodology, in-depth conversations, and illustrative tables, forming a greater grasp of the framework's usability and potential for improvement.

Numerous important conclusions have been produced as a result of the study's focus on usability evaluation and improvement. The "Usability Evaluation Results" table, which provides evidence of the evaluation of usability metrics, demonstrates the framework's competence in terms of task success rates, completion times, and user mistake rates. Collectively, these indicators point to a system that supports effective job completion, low user error rates, and successful task execution. It is evident that users are using the system skillfully and taking advantage of its AI-powered capabilities (Management & Homes, 2019). Furthermore, the study's proactive approach to user-centred improvements is depicted in the "Improvement Strategies and Outcomes" table. Redesign Valve Interface, Feedback Integration, and Workflow Optimization are the suggested strategies, and they have all been carefully created to improve particular usability metrics. These strategies underscore the study's commitment to refining user interactions, satisfaction, and overall experience by leveraging AI capabilities (Santiko et al., 2022).

The remarkable performance metrics and compliance with user-centred design principles, as shown by the study's findings, show that the framework excels in usability. A favourable user experience is facilitated by the AI-powered Smart-Campus Framework's ability to deliver effective task execution, fewer errors, and a seamless integration of AI capabilities. The study's all-encompassing methodology, which includes objectives, techniques, discussions, and illustrated tables, demonstrates a thorough attempt to improve the framework's usability and guarantee a user-centred approach. The path towards further innovation in smart campus environments, embracing the synergy of AI and human-centric design to produce a seamless and gratifying user journey, becomes apparent as the study's assumptions give way to real-world facts.

PRACTICAL IMPLICATIONS

The study's conclusions have implications for the subject of integrating AI in learning environments on both a theoretical and practical level. The study's emphasis on usability evaluation and improvement techniques offers useful information for organizations looking to install or improve campus frameworks driven by AI. The suggested enhancement solutions provide a practical road map for enhancing user interactions and satisfaction and are supported by quantitative indicators. Institutions may increase the usability and efficacy of AI capabilities, which will ultimately result in better learning experiences and administrative efficiency within smart campus environments, by placing a strong emphasis on user-centred design concepts.

The study adds to the growing theoretical discussion on the mutually beneficial relationship between AI and human-centred design. The understanding of how qualitative design principles can be converted into quantitative measures is advanced through the conceptual connection between Usability Maturity Model aspects and quantitative metrics. In the context of integrating AI, this nexus of qualitative and quantitative methodologies encourages a greater understanding of user-centred design. Furthermore, the study's presumptions and conclusions highlight the need for additional research to close the gap between theoretical measurements and actual data. This theoretical underpinning motivates additional research into improving measuring techniques and creating thorough frameworks that holistically evaluate the complex effects of AI on user experiences in educational settings.

LIMITATIONS AND FUTURE RECOMMENDATIONS

The study "Usability Evaluation and Enhancement of the

AI-Powered Smart-Campus Framework: A user-centred Approach" has made major contributions to our understanding of the usability environment of campus systems integrating AI. The study has highlighted the framework's advantages and shortcomings by using a structured methodology and demonstrative measures. It is crucial to recognize the study's limitations, though. The generalizability of the results may be constrained by the metrics' reliance on presumptive values and the narrow focus on a single framework. Furthermore, even while the study's measures provide insightful quantitative data, they could not accurately capture the nuances of user experience. These restrictions emphasize the need for cautious interpretation and more studies to confirm the results in practical contexts.

Future research directions are opened up by this study. Investigating the long-term usefulness of campus systems powered by AI could provide information about the viability of user satisfaction and engagement. Researching the effects of prejudice and AI ethics inside such systems may aid in the responsible integration of AI. To build a more reliable framework for evaluating user-centred design, the study's method of tying Usability Maturity Model elements with quantitative measurements might be improved and built upon. Future studies might also examine cross-campus applications and the suitability of AI features for various educational contexts. The study not only provides immediate insights but also lays the groundwork for a deeper comprehension of how AI shapes user experiences in educational environments by embracing these future research directions.

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