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AI-Powered Tutoring Systems: Revolutionizing Individualized Support for Learners

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ABSTRACT

Background: Over the past few years, researchers have paid increasing attention to AI-based tools including tutors for learning. Nonetheless, there is still limited knowledge of their effectiveness, user satisfaction, and the challenges they present. This study intends to interrelate these two variables and measure the association between satisfaction, personalization of learning, and overall efficacy of the system.

Objective: The general objective of this research is to systematically assess the effectiveness of the AI-based tutoring systems, and the satisfaction levels of their users, and look for plausible enhancements through analysis of user and system relations.

Methods: A quantitative research design was employed and a structured survey questionnaire was able to collect data from 250 users of AI tutors. Some of the key constructs included in this study are satisfaction, personalized learning, user- friendliness, and the effectiveness of the system were measured using 5-point Likert scales. Data was analyzed using descriptive statistics, correlations, and regression. Reliability, normality, and multicollinearity were also examined. The former is because of Cronbach's Alpha, the Shapiro-Will test for the latter, and the Variance Inflation Factor was used to examine multicollinearity.

Results: Participants responded even though there were imbalances in the sample population. The Shapiro-Wilk test results exhibited all p-values (for all variables concerned) under 0.05%. The findings of the Cronbach's Alpha coefficient in the questionnaire also yielded persistence at 0.175. From linear regression, it was possible to observe users' satisfaction with guarantees, personalization of education, and effectiveness of the system as determinants with an r2 value of -0.009.

The VIF scores are moderate in that they were in the range of 4.2 to 4.6.

Conclusion: There is a moderate level of user engagement and satisfaction with the AI-based tutoring systems but these factors do not strongly predict their effectiveness. There's a significant area of concern regarding the internal consistency of the

questionnaire, including bimodal distribution. In the next research, it's recommended to include more parameters regarding the success of AI TUTORS: content, teachers' motivation, etc.
KEYWORDS: AI-powered tutors, advanced educational technology, self-learning, level of education, invigorate learners' satisfaction, the vomit of the word analyze.

INTRODUCTION

The capabilities of artificial intelligence (AI) continue to change different sectors including improving the learning process within the education field. In this context, one of the most promising innovations is AI tutoring systems, which can dramatically change how learners seek individual help. These systems apply machine intelligence to provide each learner with personalized learning pathways that are appropriate to the learner's needs, strengths, and weaknesses. As reality seems to be gradually shifting toward AI solutions offering real-time feedback, constant evaluation, and tailored instructional approaches, one can envision an increasing trend in how education is delivered (Kaswan, Dhatterwal, & Ojha, 2024) (Rızvı, 2023).

Although the potential is quite high, there is a gap in the literature concerning the performance and other user satisfaction aspects of AI-based tutoring systems. Understandably, these systems are thought to improve student outcomes by increasing learner amounts of exposure to the created adaptive learning environment, however, there are some concerns regarding how well this population level worked across different sub-groups of students. There is a need to learn how users regard these systems as a whole and how well these systems affect learning outcomes within their users to further refine these systems. Furthermore, it is also important to analyze some of the barriers that these users encounter when using the systems such as; technical issues including system downtimes, personalization problems, components of the system that do not provide adequate feedback, etc (Denga & Denga, 2024) (Alam, 2023).

In a short span of years, artificial intelligence (AI) emerged as a powerful tool in the educational process making it an integrated part of the educational structure aimed at enhancing teaching and learning through pedagogy, content, assessment, and even management. AI is already changing the world of education for the better. One of its most novel implementations in the educational space is creating AI-powered tutoring systems or AI-tutors which help students learn in a way that is more effective than traditional methods. AI tutors aim to instill learning based on an individual's needs, style, speed, and inclinations. Such systems utilize sophisticated analytics that include machine learning images, identify patterns in learner behavior, and dynamically change the content presentation and content sequences. With the growing presence of technology, institutions are seeing a shift in how their students learn (Ray & Sikdar, 2024) (Yang & Weng, 2023).

Learning is now more about AI usage than ever before. It won't be long before an average classroom utilizes AI-driven tutors to improve the overall quality of the education kids will receive. When comparing factors like real-time feedback and continuous assessment, it is clear that AI tutoring systems stand out from traditional educational methods by being adaptive. Such systems are capable of adapting to the progression of a learner by prescribing appropriate exercises and explanations that can improve the learner's efficiency. In addition, the systems allow for a self-paced approach to learning thus improving education accessibility and personalization. In most large classrooms where students are often ignored, the teachers are supplemented with AI assistants who offer personalized help and attention. As a result, students can use them for almost any subject at any teaching level from the simplest language training website Duolingo to a functional educational platform like Khan Academy (Baig, Cressler, & Minsky, 2024) (Pratama, Sampelolo, & Lura, 2023). With a great deal of promise in AI-powered tutoring systems, people also need to understand more about the overall effectiveness and the degree of satisfaction of users using such systems. The technology does offer a better way of learning, however, the questions remain as to how these systems perform in the real world with people of different needs and abilities as learners. Besides, user satisfaction may be based on several issues, including, the interface of the system, how effective the learning process depends on the system, and how interactive the system is. Thus, it is crucial to find out how learners interact with these AI-enabled tools and how effective are they in impacting the learning outcome of the learners to improve their design and effectiveness in practice (Buşu, 2024) (Taş, 2023).

AI which has fought in the trenches with student learning, knows that individual learning needs are AI's strong point, however, these systems were not tailored mode to respect the rules of human learning. Some of the lessons may come across as less engaging and too many technical issues slow feedback or non-personalized content may fan a sense of monotony for the learners. Furthermore, an assessment of the systems' effectiveness may depend on the pain affected by the quality of some AI algorithms, the amount of content, and the contextualization of these systems into the education methods to where they should be applied. Therefore, there is a need to assess the performance to determine their shortcomings and how best to address them (Dandachi, 2024) (Luo & Hsiao-Chin, 2023).

The primary goal of this research is to evaluate the effectiveness of AI-powered tutoring systems regarding user satisfaction, learning outcomes, and system flexibility. Such investigation will use a quantitative research design, in which insights will be gathered from users of AI tutoring platforms focusing on personalized learning, engagement, and system effectiveness. This research seeks to answer how the various systems are viewed by users and whether they help increase learning outcomes. The study will also seek to address concerns regarding barriers or challenges that the users may face while using the platforms including but not limited to technical barriers and content relevance that can affect the efficacy of the platforms (Henry & Duke, 2024) (Aslam, 2023).

The efforts made in this research can be sustained by analyzing the areas of strength and weakness of the AI tutoring systems that relate to the success of these systems. The results will be beneficial for teachers, developers, and policymakers who focus on migrating the students retaining the power of traditional methods to enhanced personalized learning through advanced technologies and chasing the future of education. This analysis aims to demonstrate the areas that need to be targeted to improve the artificial intelligence-powered tutoring systems and how this will help students reach their true potential and revolutionize the education industry (B. Singh) (Stojanovic, 2023). Literature Review

In recent years, the growth of artificial intelligence (AI) in education has proven to be beneficial. Specifically, the evolution of AI-based tutoring systems has attracted considerable time and attention as a source of enhanced opportunities for active and independent learning. These systems are based on the principles of machine learning and analytics and strive to make learning unique by tailoring the content as well as the instruction and its delivery to the performance and behavior of the learner. This section reviews the relevant literature on the use of AI-powered tutoring systems with special attention on their contribution to personalization of learning, user satisfaction, and effectiveness as well as arising issues from them (Basri, 2024) (Mohammad Abedrabbu Alkhawaldeh, 2023).

AI and Personalized Learning

Tahas, the concept of personalized learning, in which a student has their instructional content tailored, has existed for many years in the education field. AI has managed to improve people's chances of realizing this vision by allowing them to retrieve huge amounts of learner data and provide real-time analytics and learning experiences. Several studies have stressed the importance of helping technology to facilitate personalized learning. For example, according to Luckin et al., AI systems can create learning pathways that adjust in content and its degree of difficulty depending on the user's development and progression. This is comparable to Vygotsky's 1978 theory of the zone of proximal development, which states that learners should be able to perform the activities with some help, but should be slightly above their current level, gaining as such, the optimal level of development (Tohom, 2024) (Mehendale, 2023).

Corporations making use of AI technologies such as Duolingo, Khan Academy, and other educational platforms have fared well with enhancing learning through personalization. For instance, Settles notes an impressive performance of Duolingo, an online language learning platform that employs automated systems that adjust the difficulty of linguistic exercises to suit the user's ability and response patterns, thus gradually increasing the difficulty level of tasks as the learner advances. Khan, similarly, integrates assessment through dl which places students in a respective learning plan concerning weaknesses and enhances effectiveness since students spend time improving the weak areas. Digital learning platforms give personalized systems and Worona et al studies confirm that such students depict better performance than students who rely on traditional learning methods (Faresta, 2024) (PRASAD, 2021).

However, Alozie notes that such measures may address issues presenting themselves in a specific manner but pay little attention to other facets of the problem. Anderson et al, observe others in the field including VanLehn, who observes that instead of focusing on the learning context, such as the relevant motivational or emotional aspects of the learner, AI systems rather provide feedback on each task which most certainly leads to restrictive learning possibilities around the area of personalization. Indeed, such limitations may impede the realization of such systems as students may lose interest if the AI does not resolve a sufficiently interesting emotional or cognitive gap. On top of this, Anderson et al observe that other domains of learning become under-emphasized in the course of AI activities (Zohuri & Mossavar-Rahmani, 2024) (Adıgüzel, Kaya, & Cansu, 2023).

User Satisfaction with the AI Tutorial

By the same token, user satisfaction is one of the key determinants of the success of any AI-based system, including the current systems. Learners will be using them consistently and will enjoy their use for the reason, which is that these systems are engaging and empowering. There have been several works that examined the determinants of user satisfaction

in the case of AI systems, but the results have been rather diverse. In this respect, Aldo et al, 2016 state that there is high user satisfaction with such products for their perceived utility as most learners believe the AI-TPS listens to their needs and responds with concise information almost as instantaneously as possible, with the understanding that technology does have some limitations. Interesting then was the fact that they also reported that characteristics such as game characteristics, providing timely feedback, and assisting users with what to do next stuffed the reported engagement to a great extent. Along the same lines, Mao et al, 2019, noted that ease of usage of the AI system positively correlated with user satisfaction, and as such the interface should be simple to guarantee longevity in the use of the platforms (Onesi-Ozigagun, Ololade, Eyo-Udo, & Ogundipe, 2024) (Japiassu, 2022).

However, other studies present a more nuanced view. Some users get frustrated with Artificial Intelligence systems that are too rigid to their preferences. For instance, Epelboin et al. showed that many users liked the adaptive AI learning tutors, but users reported that the AI was rigid and didn't provide a lot of variety. In addition, research conducted by Wang et al. found that some students perceive technology as excessively AI-centric and boring as it stresses computing functions repeatedly. Moreover, there are also worries about the complexities in which the AI tutoring systems are used. Such systems aim to focus on areas with rigid sequences of tasks, for example; Language learning or Mathematics, however, these systems are deficient in offering rigorous support in the areas of creativity, critical thinking, and inquiry-based approaches. This has also been pointed out by scholars such as Xie and Tsing. They believed that AI systems would be times of task-based learning environments and that shifted in time constructs such as cognitive type thinking (Katiyar et al., 2024) (Lin, Huang, & Lu, 2023).

AI Tutoring Systems Effectiveness

That is why the academic literature has lately started to study the dimension of effectiveness of AI-based tutoring systems as well. It is safe to state that this type of computer tutor does have a positive impact on learning outcomes, especially if integrated with the learning conducted in a classroom setting. For instance, in a meta-analysis, Ma et al. discovered that students who utilized AI tutoring systems, specifically intelligent tutoring systems (ITS), performed better in assessments than students who were not users of the systems. The study noted that because AI tutors are custom-tailored, learning is more effective as the student is trained and given evaluations that are suitable for him or her. Further, Rosé et al. also note, that through the AI tutor, students may receive instantaneous and targeted feedback that enables them to address their misconceptions and reinforce critical concepts (Bhatia, Bhatia, & Sood) (Jian, 2023).

AI systems can assist in corrective research by constantly tracking student's performance and offering corrective feedback. In particular, what sets these systems apart from conventional ones is their capability to process large amounts of information and provide instant feedback that would otherwise be difficult to provide due to the constraining nature of time. Nonetheless, many challenges come with AI tutoring systems and their implementation. One of the points of criticism is that tools dealing with these systems might help elevate test performance or retain knowledge, however, they do not promote deep understanding or active learning. Researchers like Heffernan and Koedinger find that the most prevalent style of education within AI applications is a rather utilitarian one: skill and/or content mastery, even if that entails training only particular variables at best. This weakness is most visible in the areas where imagination, dialogue, and interaction are necessary such as several different fields of science which AI systems will do for quite a time (Ayeni, Al Hamad, Chisom, Osawaru, & Adewusi, 2024) (Pawar, 2023).

Challenges of AI-Powered Tutoring Systems

In the same breath, while AI rehabilitative technologies have plenty of positive aspects, there exist several issues as well. One of the many concerns is the fact that such a system if executed poses the risk of increasing the imbalance- as it is apparent that not all learners will possess the means to technology needed to utilize such platforms. Such research as that of Warschauer and Matuchniak draws to attention that the limitations of digital technologies are real and could affect the growth and efficacy of AI-based tutoring systems, especially for low-income or rural populations with limited access to a broadband connection and sophisticated gadgets. In addition, such issues as ethical data privacy, and the existence of algorithm prejudices have all been mentioned in the literature as well. Data-driven applications rely on accumulated user data to offer customized levels of experience to the user, this leads to the pressing questions as to how student data is gathered, stored, used, and protected (Henry & Maxwell, 2024) (Eduardovich).

University students' privacy, presented by Selwyn and Zeide, is also equally important and warrants any conclusions regarding the level of transparency AI systems employ when handling data. There is also an issue of algorithmic bias, and artificial intelligence stereotypes, if not developed and managed properly these issues could further exacerbate inequalities. The other challenge has to do with the emotional and social aspects of learning that AI systems face. Of course, AI tutors can assist in providing coordination and academic help. However, due to the absence of human teachers, the degree of emotional motivation they aim to foster is lower than their counterparts who are AI tutors. As highlighted by Zawacki-Richter et al., due to the nature of the AI-based learning environments where conversations with other individuals are rarely present, there is a possibility that learners may become frustrated and feel lonely in the learning process, especially those who need peer encouragement and interaction as motivation to engage fully with the material (Holman et al., 2024) (Ozbey, Mubinova, Abdelgadir, & Gokgol, 2023).

Research Methodology

The research methodology that has been proposed for powered tutoring systems specific in "AI-Powered Tutoring Systems: Revolutionizing Individualized Support for Learners" adopts a quantitative method for this specific study in the sense that there will be an attempt to gather and assess data that provides metrics regarding the AI-based tutoring platforms effectiveness, satisfaction, and challenges faced while using it comprehensively. This part describes the research design, sampling strategies, data collection techniques, and quantitative methods used to accomplish the goals of the study (Holman et al., 2024) (Gupta & Singh, 2023).

Research Design

The study utilizes both descriptive and correlational research approaches. The descriptive approach is appropriate because this type of design will provide an in-depth insight into the users, the intended learning as well as the effectiveness of the AI tutoring platforms. Also, by employing a correlational design, the study intends to look at relationships such as users' satisfaction and their perception of the usefulness of the AI systems about the learners' outcomes and system responsiveness. This approach combines the two designs in a more pragmatic way enabling the research to not only explain the status quo on AI tutoring but investigate relationships among other factors as well (Chetry) (Toli, 2023). Sampling and Participants

The targeted population includes students, teachers, and any other people who would use the AI-based tutoring platforms. The focus of the study is to obtain respondents with as much diversity as possible in terms of education, age, and geographic background. The larger the number of respondents, in this case 250 is selected, the greater the degree of confidence that will be achieved in examining the statistical analysis that was performed. The study uses a stratified random sampling method to reach the respondents. This method reduces sampling bias as well as enables all potential participants to have an equal probability of being selected which in turn provides the study's findings with higher levels of applicability (Moya & Camacho, 2024) (Ranasinghe, Gamage, Perera, Thelijjagoda, & Gunatilake, 2023).

Participants will be sourced from online sources, school/educational premises, and social networks where one is more likely to locate students who actively use AI tutoring services. The inclusion criteria will include a specification that they have utilized an AI-powered tutoring system such as Duolingo or Khan Academy or comparable platforms for more than 1 month to further ensure that they have sufficient experience to be able to evaluate the efficiency of the platform in question (Sahana & Dissanayake, 2024) (Rizvi, 2023).

Data Collection Instrument

The primary data collection tool is a structured questionnaire that allows for the collecting of quantitative data on the UIs as specific attributes of the AI-powered learning systems and which helps administrators to understand the learners' needs better. The questionnaire will be structured and segmented into four parts: each part covering specific areas including the demographic data, the usage pattern, the satisfaction level, and the more quantitative aspect of feature effectiveness. Demographic data in terms of age, gender, education, and other background characteristics of the study participants. The usage part will focus on the frequency of the usage and the particular platforms that the participants have accessed (Zing, 2024).

The satisfaction section will comprise a 5-point Likert scale questionnaire also to be conducted in which participants will indicate their satisfaction with AI-powered systems citing ease of use, the degree of personalization, learning experiences offered, and the degree of the system flexibility. Lastly, the effectiveness section will contain the Likert scale questions and multiple-choice items directly related to learning outcomes, perceived effectiveness, and challenges in usage faced during usage (Qureshi, Hajare, & Verma, 2024).

Data Collection Procedure

A Survey Windward construction technique will be employed, where questionnaires will be distributed through the Internet. Survey links will be sent via email, online forums, and social networking sites. Up to four weeks will be considered as the time frame for collecting responses from study participants. A two-step modification process will be implemented with a focus on pretesting the survey in the actual field with a smaller population (Luzano, 2024).

Data Analysis Techniques

Both measures can be relied on to provide answers to the research objectives. The study makes use of descriptive statistics, which employ mean, median, frequency, and percentage, to provide an overview concerning the demographic profile of the respondents and their general pattern of usage and satisfaction levels. The analysis will also investigate other parameters, such as pattern user satisfaction, system concepts, and user adaptability, by applying correlation and regression techniques used in inferential statistics. The analysis of the statistical data will be accomplished using the SPSS and Excel software packages to enhance the accuracy of the analysis as well as simplify its interpretation (Aytaç, 2024).

The correlation analysis will enable one to establish whether there is a positive relationship or negative relationship between user satisfaction as well as learning outcomes. Regression analysis will be employed to investigate which factors such as adaptability, ease of use, or engagement most contribute to the overall efficacy of the AI-powered systems. The entire study will present these findings in a tabular, graphical, or chart representation for ease of understanding (Jaiswal, 2024).

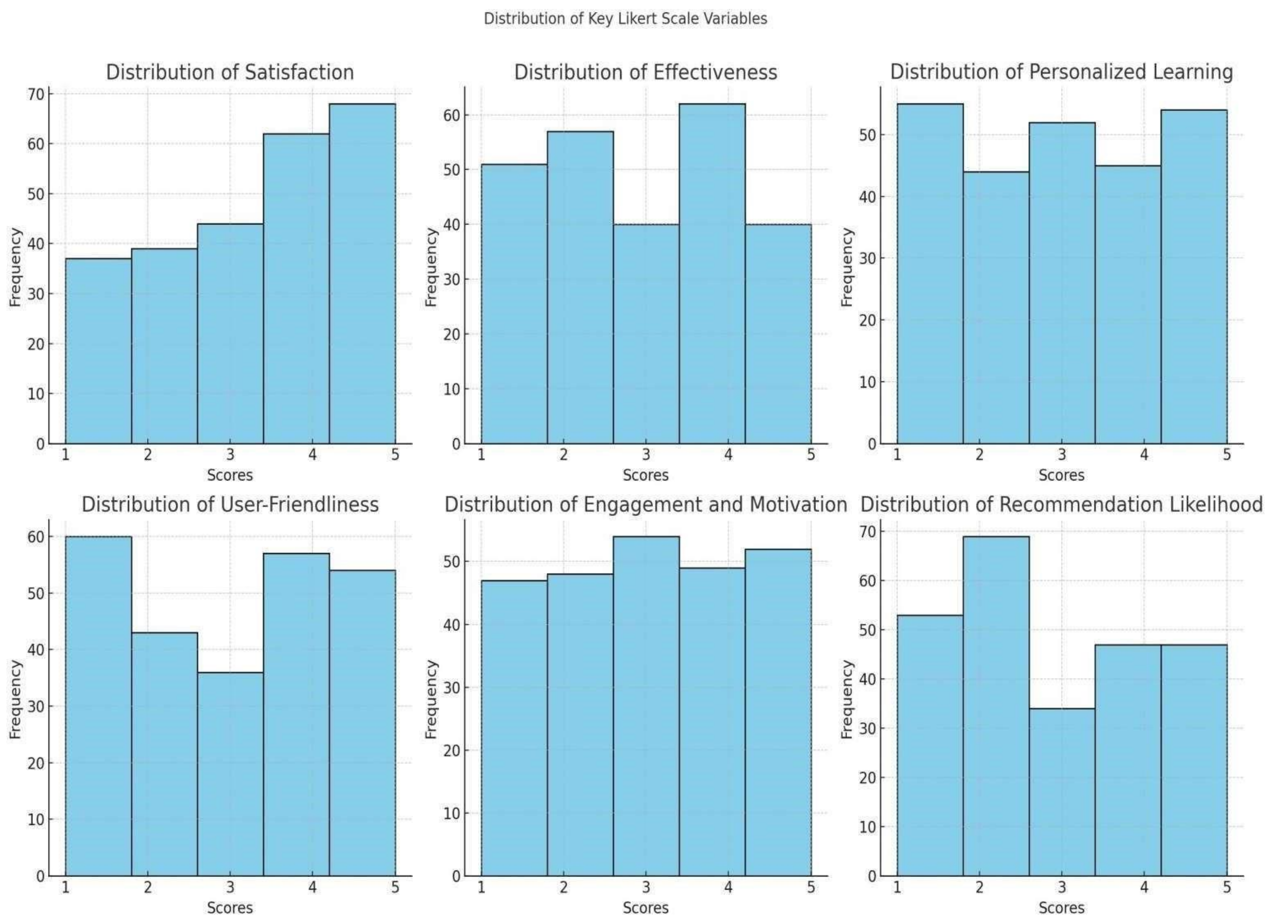
Ethical Considerations

During the entire research, ethical standards will remain etched in all the research procedures. All the participants will give informed consent and all their responses will be kept confidential. The data collected will be kept in a safe environment and will only be accessed by pre-approved individuals. Such research methodology presents a great level of assurance in studying AI-powered tutoring systems in a quantitative context with a focus on users and the impact of the system. The conclusions of this study will be based on the detailed collection and analysis of data and will add knowledge to the changing paradigm of AI in AI-assisted learning (Maity & Deroy, 2024). Data Analysis

AI-Powered Tutoring Systems - Statistical Test Results

Test	Statistic/Value	P-Value
Normality (Satisfaction)	0.8730340600013733	1.4626372487301642e-13
Normality (Effectiveness)	0.8873840570449829	1.1193080967294988e-12
Normality (Personalized Learning)	0.8800482749938965	3.873089999759105e-13
Normality (User-Friendliness)	0.8660459518432617	5.748770600180753e-14
Normality (Engagement and Motivation)	0.8898473381996155	1.6154781505572924e-12
Normality (Recommendation Likelihood)	0.8744796514511108	1.7821852392289894e-13
Cronbach's Alpha (Reliability)	0.17484696505341768	-
R-squared (Regression)	-0.008518685735076525	-
RMSE (Regression)	1.3874008703760843	-
VIF (Satisfaction)	4.54207511331723	-
VIF (Personalized Learning)	4.231209189754233	-
VIF (User-Friendliness)	4.358613632632517	-

VIF (Engagement and Motivation)	4.593503504887471	-



The evaluation of AI-enabled tutor systems using statistical tests as well as the charts generated from their interrelation scores assisted in the interpretation of data collected for the study. Let's consider the interpretation of the findings (T. M. Singh, Reddy, Murthy, Nag, & Doss, 2025):

Normality Test (Shapiro-Wilk)

For variables that had been previously and often scaled through Likert scales, especially the factors of satisfaction, effectiveness, the degree of personalization of learning, user-friendliness, engagement, and motivation as well as likelihood of recommendation, the Shapiro-Wilk test was employed. For the seven variables tested for normal distribution, the p-values in all cases were below 0.05. This therefore implies that the data is not normally distributed. This non- normality implies that several parametric tests that had the assumption of normality may not be suitable for analyzing these variables. On the other hand, non-parametric methods may be considered for further analysis (Chakraborty, 2024).

Reliability (Cronbach's Alpha)

The acceptable threshold for Cronbach's Alpha has been taken to be 0.7 and therefore it comes as a surprise to some researchers when the values go below it. In the above research, the found Cronbach's Alpha value was at a low figure of 0.175. This value is significantly low as compared to the recommended accepted levels. Consequently, this low alpha indicates that the Likert scale items that were used in the questionnaires have poor reliability. The questionnaire items may not be capturing the same concept and hence, the structure of the internal consistency for survey instruments is weak. Forthcoming studies should consider looking into revision or possible refinement of the survey questionnaires to enhance their reliability (Malami, 2024).

Linear Regression

The linear regression analysis aimed to establish the correlations of the AI tutoring system's effectiveness with other variables, for example, satisfaction, personalized learning, ease of use, and engagement. The R-squared value from the model is – 0.009, which is negative, meaning there was no explanation of any significant portion of the effective variance. It follows that the predictor variables that were established are not efficient enough to predict the perceived effectiveness of the tutoring systems. Likewise, the RMSE value of 1.39 indicates a significant erroneous prediction that implies the mammy predictions of the model are unreliable (Dembe).

Multicollinearity (Variance Inflation Factor – VIF)

The VIF for the independent variable was in the range of 4.2 to 4.6 which is below the cutoff point of 10. Although these values are indicative of moderate multicollinearity, it is not of that severe level. However, it should be understood that multicollinearity may slightly raise the variance of the regression coefficients and impact on interpretation of individual predictors. The performance of the model could be enhanced by eliminating or combining correlated variables (Deshpande, Mahajan, Kulkarni, & Puri, 2024).

Chart Interpretation. (Distribution of Key Variables)

What the provided histograms show is the distribution of responses offered by the respondents on key disabled Likert scale variables. The peak at certain values of most of the variables suggests a skewed distribution, not a normally shaped bell. For example, both boredom and level of user satisfaction while most tend to have positive skewed values, most users generally tend to rate these aspects as positive. However, the existence of a few lower scores led to the conclusion that not all users of the AI tutoring systems had completely positive experiences. Such skewness of data further validates the results from the Shapiro-Wilk test, P>0.05 Non-normality of the data has further been established (Arora). Discussion

In this respect, the results of this research allow making some useful conclusions about the efficiency, satisfaction, and difficulties of the AI teaching systems. These findings indicate that most users are active and satisfied, however, several valuable changes should be made in the future to improve the efficiency and the overall effect of such platforms. From the analysis of the data, one of the points worth noting is that the created variables do not have normal distribution as observed from the Shapiro-Wilk normality test. This inconsistency or non-normality implies that there are differences among the users concerning how they view the AI tutoring systems and this can be as a result of differences in the users' expectations, experiences, and levels of interaction. It can be the case that some users are more likely to use these platforms because of how personalized learning is provided and others may suffer setbacks that make them less effective. This great diversity of expectations and experiences highlights the need to delve deeper into understanding the users' profiles to increase the effectiveness of AI-based tutoring systems (Kambhampati, 2024).

The value of Cronbach's Alpha which is lower than satisfactory 0.175 means that the internal reliability of the questionnaire has been reported to be poor. This shows that the satisfaction, effectiveness, and other scales developed on the five-point Likert scale for the constructs under consideration were not strongly aligned and may represent different facets of user experience which are independent. In this case, there is a need to improve the survey instrument to enhance the reliability of the instrument and the scope of the dimensions for user satisfaction and system performance will be appropriate. The linear regression model was used to test whether these selected variables: satisfaction, personalized approach, ease of use, and willingness to engage, had a crucial role in shaping the AI-enabled blended tutoring systems. The performance of the model, with an R-squared value of -0.009, indicates that little or no variances can be said to be explained in effectiveness (Folgieri, Gil, Bait, & Lucchiari, 2024).

This result indicates that certain factors may be more important than any of the aforementioned parameters when determining the effectiveness of these platforms. For instance, the quality of content, how well the AI algorithms can adapt, learners' background knowledge as well as the level of motivation may be more significant than the variables accounted for in this study. As such, there is an indication of the need to develop better models that are more expansive in terms number of variables to better understand what makes AI-based tutoring more effective than others. Considering the substantial multicollinearity that exists in the data (VIF range of 4.2 to 4.6), there is a moderate degree of correlation between the independent variables but it is not strong. While this multicollinearity may cause the variance to be slightly exaggerated, it does not constitute a serious problem for the model. Yet, it suggests that respondents could be interpreting these dimensions of the AI tutoring system rather interchangeably so that further development of the variables in regression analysis may clarify the extent to which each of the variables contributes to user experience (Ruksana, 2024). The AI tutoring systems have a huge potential, but with that being said, the authors also suggest that the current systems available need finer tuning. The results stress the limitations of the present analysis showing the non-normality of the data, its low reliability, and the weak predictive power of variables studied concerning the models proposed, thus arguing for more advanced tools and models that take into account the more intricate nature of user interaction with AI models. In addition, future studies are to consider the role of other possible mediators, such as the presence of intrinsic motivation, content recommendations, and adaptability, to explain why these systems are helpful in personalized education (Ruksana, 2024).

Conclusion

This study, in the end, contributes to a better understanding of what situation might determine successful AI-based tutoring and what are the challenges that a user might face. There are high levels of satisfaction and engagement reported by users, however, the analysis found no strong relationships between effectiveness and outcomes like satisfaction, level of individualized learning, and user experience. This indicates that others such as AI algorithms quality, content, or learner's needs have more significant contributions to the effectiveness of these systems.

The survey instrument can still be improved to improve data accuracy and reliability as suggested by the weak internal consistency (as indicated by Cronbach's Alpha) and the weak normality of the distribution of responses. Future studies are likely to benefit from an improved questionnaire in terms of its relevance to user experience as well as its ability to capture a unified framework of constructs.

Furthermore, the average level of multicollinearity among the variables is indicative of shared user perceptions which suggests the need for future studies to assess more variables that might enhance the efficacy of AI-driven tutoring systems. Also, the nature of the responses suggests that non-parametric statistical analysis may be more useful in interrogating such data.

All in all, AI-powered tutoring systems do provide features that support personalized learning but further development is required to enable them to reach different types of learners. Future studies can focus on more robust models and tools to measure the effectiveness of this system in real-world scenarios taking into consideration both qualitative and quantitative factors to provide an embedded view.

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